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HOW CAN ARTIFICIAL INTELLIGENCE SHAPE THE FUTURE OF SUSTAINABLE EDUCATION? CHALLENGES AND OPPORTUNITIES

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ABSTRACT

Artificial intelligence (AI) is bringing about a significant transformation in the educational process, making it more personalized for each student and enhancing their engagement with content while reducing the time spent on administrative tasks such as attendance tracking and exam grading. AI-powered systems can analyze student behavior, identify learning patterns, and provide personalized feedback, creating an adaptive learning environment that responds to each student's needs. This study aims to review current research on the use of modern AI technologies such as machine learning, deep learning, and natural language processing in education. The study summarizes the challenges associated with these technologies. Additionally, the study suggests improvements for each of the challenges discussed, focusing on creating more robust, transparent, and equitable AI systems. It also summarizes the key databases used to build AI models in education, highlighting their role in enhancing the accuracy and efficiency of AI-driven educational tools. Despite the vast advancements in AI-based educational technologies, there remains a critical gap in understanding how these systems can equitably benefit diverse student populations and ensure ethical implementation. This study not only examines existing AI applications but also critically evaluates their limitations, particularly in ensuring fairness, reducing biases, and maintaining transparency in decision-making. By addressing these concerns, this research contributes to the ongoing discourse on improving AI-driven education systems to better serve students from various backgrounds and learning capabilities. This study is expected to contribute to the development of AI applications that not only improve the quality of learning but also provide a more efficient, equitable, and interactive learning environment that supports both educators and students.

Keywords— *Artificial Intelligence; Sustainable Education; Deep Learning; Machine Learning*

1. INTRODUCTION

AI is a branch of computer science that requires the development of computer systems for tasks such as learning, reasoning, and decision-making that require human intelligence. It works to automate the most complex processes within various industries and provide deeper insights into data analysis. For education, artificial intelligence is crucial for personalized self-learning experiences by adapting to individual student profiles; thus, improving overall efficiency and productivity in teaching while alleviating the burden that traditional educational methods typically impose on resources [1]. AI systems continue to bring significant benefits to sustainability in education by analyzing student data to create experiential learning scenarios for each student. These systems help students learn more effectively while requiring less time and resources compared to traditional teaching methods. For example, AI can be used in personalized learning systems, intelligent chatbots that respond to student inquiries, and real-time performance monitoring to prompt teacher intervention and create a dynamic and responsive learning environment [2]. Related to AI applications in education, several recent studies have explored deep learning and transfer learning techniques across various domains, providing valuable insights into their potential for enhancing intelligent learning systems. For instance, a novel transfer learning approach has been proposed for classifying hand-drawn mathematical geometric shapes, demonstrating how AI can improve pattern recognition and interpretation [3]. Deep learning has also been leveraged for detecting bone fractures using radiographic images, reflecting the importance of these techniques in analyzing complex medical data and making accurate decisions [4]. In the context of cognitive understanding, a computational model has been introduced to study cognition dynamics in cases of cognitive insomnia, which could contribute to the development of educational strategies that consider students' cognitive factors [5]. Additionally, effective AI methodologies have been developed for the early detection of cybersecurity threats such as XSS and SQL Injection attacks, reinforcing digital security within e-learning platforms [6], [7]. Furthermore, a transfer learning-based model for driver drowsiness detection using eye movement behavior has been proposed, indicating the potential of these technologies in analyzing student engagement in smart educational environments [8]. These studies highlight the power of AI in processing and analyzing data to support adaptive and personalized learning, ultimately fostering a more efficient and sustainable educational ecosystem.

Artificial intelligence, the buzzword of today, has become the backbone of many educational innovations in the current scenario. Increasing research efforts are directed toward integrating machine learning, natural language processing, deep learning, and other AI subfields into the design of educational environments. These systems are intelligent learning platforms designed to assess student proficiency and accommodate different learning styles by utilizing emotion tracking, behavior analysis, and real-time interventions that enhance student motivation and academic performance [9]. Numerous previous studies have examined various aspects of using AI applications to enhance student performance and learning experiences. Many recent studies have also explored the existing gaps and strengths. Additionally, several studies have discussed how AI technologies can be integrated into curricula and school systems and assessed their impact on academic achievement, motivation, and engagement to establish a solid knowledge base within educational institutions [10]. However, despite the growing integration of AI in education, there remains a critical need to examine its ethical, practical, and pedagogical implications. Many existing AI-driven learning systems face challenges related to algorithmic bias, lack of transparency in decision-making, and the potential reinforcement of educational inequalities. This research seeks to address these concerns by evaluating the effectiveness of AI applications while also critically assessing their limitations in ensuring fairness and inclusivity within diverse learning environments. However, even with the significant progress, there is still a strong demand for further improvement of AI models so that they can more accurately monitor student engagement and provide timely intervention for their needs [11]. Furthermore, existing literature has primarily focused on the technical aspects of AI implementation, with limited emphasis on the broader impact of these technologies on pedagogical strategies and student well-being. This study aims to fill this gap by not only reviewing AI applications but also identifying key areas where AI can contribute to more adaptive, equitable, and student-centered learning experiences. Although AI technologies have already begun transforming education by enabling personalized learning and real-time performance monitoring, there are still significant gaps before fully harnessing their potential. This paper aims to address these issues through a critical review of what is currently achievable through AI applications in educational environments, identifying the strengths and weaknesses of the methods used so far. The structure of this paper is as follows: In the literature review section, previous studies are discussed, and in the summary section, the weaknesses and recommendations are summarized. The data used to train each model is also presented, along with a description of this data. Conclusion section concludes the main points of the paper and gives some future directions.

2. LITERATURE REVIEW

The article [12] deals with the implementation of AI in intelligent tutoring systems to achieve a sustainable environment for learning. Its literature survey is also comprehensive, exploring the evolution and applications of numerous artificial intelligence techniques such as machine learning, deep learning, and natural language processing. Such technologies allow learning experiences that are personalized, broaden student engagement while decreasing the hurdles to education. The review notation further addresses other issues of challenge such as privacy concerns and the application of algorithmic bias, as well as the technical hurdles of acquiring new technologies vis-a-vis existing systems within educational fields, and again throwing light on the prospects given by future innovations to developing more inclusive and sustainable educational environments.

The application of AI in education to support sustainable development is examined in study [13]. It might classify the present integration of AI technologies into different categories: cognitive services; virtual/mixed/augmented reality; IoT and edge computing; and metacognitive scaffolding. While doing this, the study discusses how these technologies can enable effective personalized

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learning experiences and, at the same time, resolve challenges such as data privacy, data quality, restricted AI functions, and legal-ethical concerns.

The authors in [14] pointed out how there was a paucity of long-term studies that were focused on the assessment of the very genuine effect of particular interventions or technologies over a long time. They stressed the need to pursue such studies in order to see how such interventions fare over time, especially in domains like education, health care, or technology. The paper reviewed existing research techniques and emphasized the need for broader evaluations that transcend short-term results in assessing sustained outcome.

Beyond [15], the research systematically reviewed the literature on the adoption of AI in education, espousing its opportunities, benefits, and challenges. AI technology such as intelligent tutoring systems and smart content offers promising personalized learning enhancement and administrative benefits. On the contrary, the reviewed literature has identified major challenges, as specified by the Technological–Organizational–Environmental (TOE) framework, such as data quality and privacy, organizational readiness and infrastructure, and ethical socio-economic considerations. The study emphasizes that clear policies and more empirical research, specifically in contexts beyond developed status, would be required to realize AI's full potential in reforming educational practices.

The area of research in [16] deals with opportunities and challenges encountered when instituting AI and machine learning (ML) in higher educational institutes. Bringing together literature reviews and a survey conducted amongst the students in Serbia, the study analyses how these technologies can improve personalized learning, skill development, collaborative environments, institutional efficiency, and research accessibility. Furthermore, the paper lists key challenges of integration into higher education that would include privacy issues, ethical concerns, and organizational and technological barriers. It provides insights and recommendations for the successful integration of AI and ML in higher education for a more innovative and competitive academic environment.

In [17], researcher assessment is on how AI is affecting education by conducting an extensive review of scientific literature. A qualitative approach was undertaken, whereby the analysis of published articles was done to elicit the applications and effects of AI in three major areas: administration, teaching, and learning. The results show that AI has immensely cushioned the efficiency and effectiveness of administrative tasks including grading assignments and giving feedback, the application of intelligent educational systems and technologies such as virtual reality and educational robots improved the quality of teaching, while AI assisted in customizing educational curricula according to the needs and abilities of each student to enhance the learning experience and some retention. From the study, it is concluded that AI affects education positively across a wide spectrum; the recommendation is to integrate AI more into educational and administrative processes and to develop policies promoting optimum use while taking into consideration its potential challenges.

The research covered in [18] offers an evaluation of how AI technology has shaped the interactions between instructors and students in the teaching of online courses. In evaluating three AI-based software tools with the aim of discovering the platforms' impact on teaching methods and learning engagement, as well as their instructional effectiveness, AI interacts with students and teachers within enriching pedagogical engagements by way of early feedback assessment combined with customized creation of educational arrangements.

According to the study presented in [19], Artificial Intelligence training technologies enhance student engagement and outcomes in learning. AI technology generates positive effects on student participation and educational achievement when a research sample of 500 students distributed across five Lahore universities employs it. AI applications can enhance structured learning, which thus impacts student creativity and academic emotions. For example, the research study [20] considered how AI-based educational applications influence creativity and academic emotions of college learners, and elicited positive results regarding students' learning outcome effects.

Application of AI within educational applications has augmented a marvelously transformed learning environment with new opportunities and challenges. Academic research argues that AI tools, to a greater degree, strengthen the capabilities of structured learning, while they produce very complicated effects on students' creativity and academic emotions. The particular event has been addressed using a mixed-methods research design that included qualitative interviews and a quantitative study with a total of 120 participants, as stated in [21]. Authors revealed that usually, AI applications impose rigid frameworks that inhibit creative thinking and innovations and lead to students' emotional detachment, because of very

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repetitive and impersonal nature of such interactions with AI. In addition, constant AI assessments raised performance anxiety, and increased emotional frustrations thwarted performance during the learning process. On the other hand, AI applications encouraged creativity through the introduction of new ideas and techniques for solving problems, made learning more attractive through interactivity, provided personalized feedbacks, and advanced emotional well-being through gamified elements and constant availability. In addition, quantitative data could also affirm that the teacher and students have positive attitudes toward the benefits and challenges of these applications. creativity based on the way practitioners utilize this technology. Such studies suggest that thoughtful embedding of AI tools would thus enhance human interactions in educational contexts toward both 'better engagement and learning outcomes'.

Research indicates that appropriate applications of AI technology make better human interaction with educational practices from students improving engagement with improved academic results. Students together with faculty members showed positive perceptions of AI-integrated programs according to [21] but also accepted both good and shortcomings of such applications. Research proves educational success to be dependent on developing the right equilibrium between prescribed AI-assisted activity and free exploration, combined with higher-level thinking skills. AI needs to be implemented and scrutinized in its application strategies by the concerned stakeholders to reap maximum benefits for superior outcomes in combining creativity with emotional involvement in education.

This certainly is research that points at risks of extracting specific human elements from education and universities that rely too much solely on automated systems. The researches claim that AI systems will still necessitate human supervision to maintain the social-emotional characteristics of teaching-learning activities. The authors assert that AI looks promising for online education, yet careful consideration must be given while applying it to improve human teaching methods instead of removing them from educational processes.

By comparison, the research [22] studies the rise in optimistic perceptions about AI becoming involved with education. AI would be able to innovate teaching as well as administration and to move toward data-driven decisions for education. Such artificial intelligent systems raise new challenges concerning information protection that are available and potentially equally relevant for learning systems concerning the ways in which algorithms would cause treatment inequalities. Universal acceptance of AI systems mostly tends to pay attention to progressive technology instead of teaching well along with the bridge to the end students and educators. The present study is devoted to matters of ethics that AI education raises together with an examination concerning the demand for open view towards AI and its equal accessibility. Research shows that AI has aroused considerable public interest, away from its adverse effect toward preserving social disparities and shaping teaching-centered instruction methodologies. The author demands a responsible way of studying AI education while enhancing regulations for maintaining ethical practices toward mentoring by teachers for critical thinking and emotional competency cultivation.

There are beneficial aspects of AI in education along with challenges to the student development of analysis and creativity. The personal learning and interactive experiences from the use of AI technology would be a benefit; in contrast, misuse of AI tools almost certainly portends the decline of a student's capability with respect to independent problem-solving. A systematic review in the study [23] shows that students with excessive reliance on AI dialogue systems find it difficult to attain the competence of critical skills such as decision-making, analytical reasoning, and critical thinking. Anyhow, research in [24] showed that when properly used, AI systems enable students to foster their critical thinking. According to the Cambridge University Press, the AI technology helps the students to think critically by means of assumption testing and deeper educational engagement. Likewise, [25] supports that students get aided by AI in enhancing creative thinking since the AI tools make the creative process more explicit and accessible thus allowing them to overcome barriers and articulate their own perspective. The best way to maximize the benefits from the use of AI in education is the incorporation of a balanced approach. Instructors must embrace AI technology as an economic teaching aid rather than in replacement of traditional teaching methods; this ensures that the essential human instructor's engagement is maintained. Mixed use of AI technologies enables students to maximize AI advantages while retaining the ability to solve real-world problems using independent methods.

On the other hand, according to study [26], personalization of education, office work

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automation, and generation of data-based decision capability are among AI capabilities. The report illustrates how AI tools, such as intelligent tutoring systems and adaptive learning platforms, personalize educational content for the specific needs of individual students to enhance student learning outcomes and engagement. It recognizes that AI helps professors by automating their administrative work, so they may solely concentrate on training students to think critically.

In its official document, there are indications of the challenges coupled with security threats that accompany the application of AI in Education systems. Apart from that, they said document has security problems together with other issues that arise as a result of AI application in educational frameworks. This report discusses the other aspects of the privacy threats stemming from the sharing of personal data and the bias issues in education technology besides possible new educational divides emerging. The Department working on the promotion of ethical AI practices through policies that allow students to benefit equally from transparent systems includes the development of recommendations or the last recommendation itself has to do with such collaborative research initiatives by concerned stakeholders to conceive organizational frameworks integrating modern automation methods with traditional educational principles. On the other side, the European Commission [27] recognizes that educational institutions require specific policies and frameworks regarding the ethical use of AI into their work. These codes of ethics have been made public to help the teachers understand the opportunities and threats which AI and data systems in education can bring. The guidelines prepare educators to work with AI systems positively critically and ethically so that they can realize their full functionality.

Besides this, education professionals should attend the requisite professional development and training. The European Network for Academic Integrity (ENAI) [28] strongly propounds that educators should be trained in AI ethics for the right articulation of learning materials and assessment practices. Such experts, however, advise on new national as well as institutional policy formations that would plug AI considerations into such processes of formulating or revising existing guidelines. General ethical standards and specialized training programs for teachers remain vital building blocks of proper introduction of AI in education-learning environments.

Besides that, the study [29] gives comprehensive insight into the effects of AI technologies on higher education by looking at ethical implications, social factors, and educational factors. In their work, the authors identified three key roles for artificial intelligence: to customize teaching for individual needs, to enhance university administration, and to expedite the research process. Rapid deployment of AI generates several complicated ethical issues entailing violations of privacy involving academic data, unfairness through algorithmic bias, and surveillance based on security. The study states that AI is an opportunity for all in education; however, its implementation needs to be done in an impartial manner so that it does not worsen inequality. On the other hand, the study also looks into how AI influences the relationship between students and teachers, academic conduct codes, and responsibilities of educational workers. This study strongly argues that technological advances should be held tighter to traditional education practices to allow critical thinking and interpersonal asset depreciation. The authors demand that principles and institutional guidelines be put in place to guide ethical integration of AI systems by universities to maintain equity and inclusive service for lifelong learning as their primary values.

We therefore look in the study [30] at how the digital divide impacts student access to technology and how this affects educational outcomes. Data from surveys with 400 respondents were obtained to create quantitative findings across distinct educational strata. There is a marked difference in digital access among groups of students, which is causing worsening academic results for students. The research pointed out that there should be strategic schemes for equal beneficiary access to technological services and training programs for students to bridge the existing educational gaps. The authors of [31] studied current divisions of AI through scientific but also patent publications that can be indicators measuring research and innovation production. The study uncovers uneven access to AI technology that demands explicit policies to engender equitably distribution and use of AI resources in educational institutions. In summation, the earlier researches endorse strategic planning to be engaged to safeguard educational data while fairing access to educational technology implements training courses concerning the faculty and students' use of AI in education.

On the contrary, research [32] probes how AI technologies can most effectively alter the educational practices within schools via "AI in Education and Schools." It states that AI tools such as intelligent tutoring systems, automated grading, and adaptive learning platforms have made teaching effective in facilitating an ever more efficient learning process. The technology has shown increased effectiveness in improving student performance and classes when creating individual teaching-learning plans aligned with unique student abilities. The results establish AI as an important development for teachers' freeing time from administrative aspects, leaving more time for the interactive and pedagogic functions of education. Moreover, this study provides the issues and barriers faced during the incorporation of AI in educational contexts. Ethical issues and data privacy have been viewed as worrying since appropriate technological tools are used to create a widening gap between students who differ with respect to availability of digital resources. Research has acknowledged proper execution of AI technology as taking custody of cooperative functions between human instructors and their traditional educational practices. It insists on the need for training in educator style that will enable school staff to merge AI tools with traditional human teaching methods into the classrooms.

The two-edged sword, as shown by the authors in their papers [33], is that AI in education could deliver improvements in equity, as opposed to worse cases where it might exacerbate pre-existing disparities in education. The authors argue for a harmonious performance between teachers and AI, meaning AI should be a teaching assistant complementing human teaching practices in delivering individualized instruction. The authors have called for fair regulation for the complete availability of AI technology devices to avoid creating a divide in schools in terms of their technological advancement.

In addition, work [34] also studied teachers' perceptions of AI in the K-12 educational setting, finding that teachers view AI as less replacement of their teaching work but more as a complement through activity management and personalized learning. Based on the researchers' analysis of AI's limitations in social functions, they suggested that use of AI should not be over-dependent because of students' need for human emotional and social support by their teachers. On these same lines, policies should also be developed and designed to train educators on how to use properly ai technology so that all students will benefit from the advances in ai without leaving behind any school in form of technological infrastructure.

Collectively, these findings suggest that AI can add educational value when incorporated into design to strengthen teaching functions in their immediate classrooms. Regarding policy, all educational institutions should ensure that their students are not deprived of equal access to AI technology because that ensures that every school benefits from outcome-improving tools that do not further amplify current distribution gaps.

Educational Data Mining (EDM) and Learning Analytics were investigated in [35], who have employed both techniques to understand the student behavior and sharply improve learning achievement. They obtained intelligent tutoring system data with such parameters as clickstream data, time on task, correct and incorrect answers, and number of tries. Employing AI algorithms designed to identify patterns such as students "wheel-spinning" and who otherwise might require intensive intervention, the analysis can predict student success based on his or her interactions with the system to design adaptive learning strategies.

According to [36], the authors present the PSLC DataShop, a new repository for educational data mining. Detailed interaction data are collected from students that use intelligent tutoring systems including their problem-solving steps, time spent on each step, right and wrong answers, and those that include changes in their changes of problem-solving strategies. This kind of data was used to create AI models oriented to predicting student behavior-for example, at-risk students and types of effective versus non-effective learning strategies. Hence, it provided grounds for developing adaptive learning systems engineered toward individual-specific use.

In [37] the authors present an improved Knowledge Tracing (KT) model-KT-IDEM, which brings item difficulty into the analysis of student behavior. Data were obtained from adaptive learning systems based on question responses, question difficulty levels, and attempts of students on these questions. The AI model considered this data to determine the knowledge level of a student and predict the possibility of correct responses in the future. The study therefore emphasized that the consideration of question difficulty is vital in analyzing student behavior and developing personalized learning paths.

The authors in [38] have investigated the question of "wheel-spinning," that is, when a student cannot seem to learn a skill despite innumerable attempts at doing so. The subjects of this study were attempts at time spent trying and the learning strategy used in intelligent tutoring systems. The researchers used AI methods to identify students who demonstrate a wheel-spinning phenomenon and to study contributing factors to this phenomenon. Findings

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from this study would lead to new insights into interventions to assist students with learning barriers in improving their performance.

In [39], the authors work on the construction of user models for exploratory learning environments using a hybrid approach combining unsupervised and supervised classification techniques. The data on interaction from educational systems like those from mouse movements, clicks, time spent on an activity, and the results of correct and incorrect answers were used in this study. The AI models analyzed this data and identified behavioral patterns, such as effective versus ineffective strategies for exploration. The study shows how AI can provide personalized feedback and support to learners engaged in open learning environments.

In [40], artificial intelligence-based learning analytics have been used to analyze the behaviors of students in massive open online courses (MOOCs). The study included data such as patterns of videos watched, quiz performances, forums participations, and assignment submissions. The researchers have performed clustering algorithms to identify subpopulations of students, such as displuming, course rejecters, and the ones who persisted to the end. The results were helpful in guiding educators on designing interventions meant to improve student engagement and retention in online learning environments.

The study describes a novel online education framework based on facial expression recognition to assess and evaluate remote students' emotional states. Due to the existing challenges posed by the lack of face-to-face interaction, the system captures students' pictures at regular intervals and processes them using deep learning developed on a modified architecture called ResNet-50. In the improvements, changes were made to the down-sampling modules and incorporated a Convolutional Block Attention Mechanism (CBAM), which together aided in better feature extraction and recognition accuracy. The technique was verified on standardized datasets such as FER-2013, RAF-DB, CK+, and KDEF to demonstrate that their approach was robust under a variety of imaging conditions and real-life use scenarios. The system monitors several indicators of a student's emotional state, including focus, difficulty, engagement, and involvement, adjusting their teaching methods based on those states. The experimental results revealed that the enhanced model produced good accuracy and efficiency across different platforms ranging from GPUs to CPUs and resource-constrained devices such as Jetson Nano, thus ensuring its practicality for real-time applications. In conclusion, their work shows that the incorporation of deep learning-based facial expression recognition in online learning setups could greatly enhance the educational process by providing immediate feedback and tweaking the instructional content to address the emotional and cognitive needs of students; it also walked through possible improvements for a better system going forward.

In [41], this research presents an online educational platform that uses facial expression recognition technology to monitor students' progress in the classroom. Periodically, images of students are captured using a camera, processed to extract facial data, and their learning status is assessed through expression recognition techniques. The accuracy of facial expression recognition is improved by utilizing ResNet-50 for effective feature extraction, with adjustments to the residual down-sampling module to enhance the correlation among input features and reduce feature loss. Additionally, a convolutional attention mechanism module is added to minimize the influence of irrelevant areas within the feature map. The proposed method achieves accuracy rates of 87.62% and 88.13% on the RAF-DB and FER2013 expression datasets, respectively, outperforming existing models. This approach enhances the detection of students' learning states and expression variations, and its application in online learning can optimize teaching strategies and resources, improving the overall quality of online education. The model was benchmarked against state-of-the-art techniques using the FER-2013, CK+, and KDEF datasets.

In [42], the study aims to establish a real-time engagement detection system for online learning based on deep learning-based facial emotion recognition. The training and evaluation of these models were done using benchmark datasets such as the FER-2013, which consists of 35,877 gray images (48×48 pixels) labeled with primary emotions including anger, disgust, happiness, sadness, surprise, and neutral; CK+ for laboratory-based settings, providing color images accurately annotated for several emotional expressions; RAF-DB considered a large-scale dataset of colored facial images in natural scenes, giving variability in illuminations, poses, and expressions; and a custom dataset that offers real-world data for the training and validation of these models by collecting information from online learners in an actual e-learning session. By combining all the datasets, state-of-the-art facial expression recognition deep learning models, such as Inception-V3, VGG19, and ResNet-50, were trained to accurately extract facial features to classify emotions from the offered data, whereby public and custom data combined to improve the system's robustness to achieve high accuracy assessment whereby ResNet-50 achieved an amazing 92.32% accuracy in the classification of facial emotions which in turn aids in the detecting of students' engagement instantaneously.

In a broad sense, in [43], the research offers a sustained survey encompassing AI-based FER systems stipulating the significance of datasets with high quality and diversity for training the respective robust model. The present study addresses the variability in facial expressions seen among adults, children, and elderly persons by investigating the datasets containing different age groups. For adult FACE recognition, datasets widely used in the field, such as JAFFE, FER2013, CK+, Radboud Faces Database NVIE, AR Face Database, AFEW, and AffectNet, are discussed as a mix of controlled and in-the-wild images capturing a wide variety of expressions in different conditions, best suitable for evaluating both traditional and state-of-the-art FER models. In terms of emotion recognition in children, datasets including LIRIS, DEFSS, NIMH-ChEFS, Dartmouth Database of Children's Faces, CAFE, and EmoReact have been cited since their strengths include capturing spontaneous and natural expressions among the younger populations, along with issues regarding imbalance and collection of data. In the other area, the surveys look into datasets like Tsinghua Facial Expression Database, Database for Emotional Interactions with Elderly, and FACES that are necessary in developing an understanding of age-motivated facial dynamics for senior citizens. The paper states that the selection and use of these datasets are determined by their specific features—from image quality to recording environment to demographic diversity—all critical variables in making an accurate and generalizable FER system for a broader range of real-world applications.

An overview of the present study is made in [44]. It presents a comprehensive survey of AI-based FER application systems, underlining the significant effect of training robust models on quality and varied dataset types. The study reviews datasets across the age continuum to consider differences in facial expressions between adults and children, as well as between adults and senior citizens. In adult FER, the paper discusses the widely used databases of JAFFE, FER2013, CK+, Radboud Faces Database, NVIE, AR Face Database, and AFEW and AffectNet that present cross-sectioned datasets collected from controlled and in-the-wild conditions, all of which are compelling for measuring traditional and most state-of-the-art FER models. On children's emotion recognition, datasets such as LIRIS, DEFSS, NIMH-ChEFS, Dartmouth Database of Children's Faces, CAFE, and EmoReact are stated as collecting spontaneous scenes and natural expressions from younger populations. Due to balancing and collection difficulties, they may not produce sufficient data for analysis. For seniors, datasets explored in this report include the Tsinghua Facial Expression Database, Database for Emotional Interactions with Elderly, and FACES, which measure age-specific facial dynamics. It notes that the selected and used datasets have specific relevance transformed by criteria - image quality, recording environment, and demographic diversity - for developing accurate and generalizable FER applications into different real-world paradigms.

The study in [45] undertakes a detailed analysis of facial expression recognition (FER) systems based on deep learning convolutional neural networks (CNNs), with specific focus on the data sets used to train and validate these models. This study describes various popular datasets such as JAFFE, FER-2013, and CK+, which are favored due to their settings and annotations of basic emotions. Comparatively, AFEW and AffectNet are datasets collected from the AFOG related conditions found in real life where indirect lighting matters, pose, and expression vary greatly. The review highlights that these datasets are indispensable to training robust FER models; they provide varying quality and conditions of images mimicking the complexities seen in real life facial expressions. Thus, it was stated by the author, the direct selection of the datasets with evaluation and testing about performance and generalization of the FER systems was emphasized, thereby addressing the need for more balanced and comprehensive datasets-especially for those underrepresented such as children and senior citizen populations-to tackle issues such as data imbalance, occlusion, and demographic diversity.

The research carried out in [46] presents a unified deep-learning framework for the recognition of facial expressions (FER) meant for diversified applications ranging from e-Healthcare, social IoT, emotion AI, cognitive AI, etc. To evaluate the performance of the framework comprehensively, the authors experimented with four benchmark datasets: the Karolinska-directed Emotional Faces (KDEF) database, GENKI-4k, Extended Cohn-Kanade (CK+), and Static Facial Expressions in the Wild (SFEW). KDEF was used to perform the evaluations on FER under controlled conditions and

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with balanced emotional representations on images from 70 subjects with different pose variations across seven expression categories. GENKI-4k, consisting of 4000 images labeled as "happy" or "non-happy," was used for binary emotion classification to highlight the system's ability to identify positive expressions. CK+ offered dynamic data in the form of video sequences of 593 productions featuring elderly to middle-aged participants aged 18 to 50 years, which were used to examine the performance of the FER system in sequential controlled settings. SFEW finally contributed 700 images that were extracted from unconstrained videos encompassing seven expression classes, enabling the evaluation of real-world scenarios characterized by various lighting, occlusion, and pose perturbations. Overall, the datasets employed contribute to a thorough performance evaluation of the proposed FER system in controlled and in-the-wild settings.

3. SUMMARY

The enlisted weaknesses or problems found in the various studies concerned with AI in education are summarized in Table 1 and are followed by the recommended solutions or strategies to counter them. Table 1 summarizes key challenges noted regarding the current use of AI in educational environments and prescriptive recommendations for remedial steps. It places forward critical concerns such as divergence of an ideal sustainable education vision and its practical execution, privacy and fairness issues arising from huge-scale data collection, and the need to have accessible high-quality and diverse datasets for effective AI model training. Other challenges include the possibility of bias in decision-making, the misalignment of the AI techniques with theories of education, the difficulties in solution portability across different platforms, and the lack of long-term impact evaluation studies. Furthermore, the recommendations depict concerns related to the limited attention given to designing human-centered AI, the neglect of advanced technical models, and the danger of grossly reducing meaningful interaction between educators and students. Key recommendations highlight the need to invest in a robust infrastructure, develop clear policies and ethical guidelines, enhance the quality of data, and promote cooperation between technological developers and educationalists. These would lay the foundation for the aim of AI being not just an enhancement to teaching and learning but promoting equitable, transparent, and effective educational processes.

Table1 Summary Of Identified Weaknesses In Ai In Education And Recommendation

Study	Problem / Weakness	Recommendations
[12], [13], [15], [16]	-Gap between the ideal vision of sustainable education and practical reality. Challenges related to available resources and technologies. Lack of awareness about the concept and applications of sustainable education.	- Invest in more efficient infrastructure to support AI technologies. Enhance awareness and institutional support for adopting sustainable education approaches.
[12], [13], [15], [16]	-Concerns Related to Privacy, Reliability, and Fairness. Large-scale data collection raises issues of privacy protection and data security. Lack of adequate policies to ensure the reliability of technologies and achieve fairness in learning opportunities.	- Implement strict policies and controls to protect privacy and secure data. Ensure transparency in how AI is used to guarantee reliability. Promote fairness in AI usage to prevent bias and ensure equal learning opportunities.
[12], [13], [16]	-Need for Large, High-Quality Data to Train Machine Learning Algorithms. Models rely on large and diverse datasets. Some educational environments lack an integrated system for continuous data collection.	- Build diverse and comprehensive databases to enable models to learn on a broader scale. Improve data quality to enhance model accuracy. Encourage continuous and systematic data collection to improve the effectiveness of intelligent systems.
[12], [13], [16]	-Potential Bias in Algorithms and Lack of Transparency in Decision-Making. Machine learning algorithms may introduce bias against certain student groups. The "Black Box" problem makes it difficult for teachers and students to understand why the system makes specific decisions.	- Design fair algorithms that reduce bias and promote equality. Provide training for teachers and students to understand how algorithms work and interpret their outcomes. Adopt Explainable AI (XAI) mechanisms to mitigate the Black Box issue and increase transparency.
[12], [13], [15]	Limited Alignment Between Technologies and Educational Theories. AI algorithms are often developed in isolation from educational foundations. Poor communication between tech experts and educational experts leads to systems that do not align with teaching methodologies or actual learner needs.	- Involve educational experts in system design to ensure alignment with effective teaching theories. Integrate educational foundations with AI technologies to enhance system effectiveness. Promote collaboration between technological developers and educational experts to develop comprehensive educational solutions.

[12], [13], [15]	-Difficulty in Porting to Different Platforms or Institutions. Developed systems may only be compatible with specific technical environments. Lack of common standards makes it difficult to transfer and apply solutions across different educational institutions.	- Support customizable and scalable solutions that consider different technological infrastructures. Develop standardized frameworks and criteria to facilitate the transfer and application of solutions in diverse educational contexts. Improve system design to be adaptable to various platforms and institutions.
[12], [14]	-Few Long-Term Studies to Evaluate Real Impact. Most research focuses on short-term or limited-scale experiments. It is difficult to determine the actual contribution of AI to sustainable education development without tracking metrics over extended periods.	- Conduct long-term follow-up studies to assess the sustained benefits and impact on students. Design longitudinal experiments that include extended timeframes to monitor results. Develop measurable performance indicators for the long-term evaluation of AI's impact on sustainable education.
[12], [13],	-Partial Focus on Human-Centered AI- Adoption of Human-Centered AI concepts remain limited. Need to consider psychological, social, and educational aspects when developing systems to ensure acceptance and effective use.	- Adopt Human-Centered AI concepts to ensure the consideration of teachers' and students' needs. Design AI systems that account for the psychological and social aspects of learning. Increase focus on human factors in the development and implementation of AI technologies in education.
[12], [13],	-Limited Adoption of Advanced Technical Models. Limited use of advanced machine learning models like Transformers and Reinforcement Learning. Applying these models requires technological investment and infrastructure that may not be available in all educational institutions.	- Encourage the use of advanced machine learning models such as Transformers and Reinforcement Learning in educational systems. Invest in research and development to implement advanced models in educational environments. Provide technical and infrastructural support to educational institutions to facilitate the adoption of new technologies.
[18], [19], [20], [21]	-Risk of reducing meaningful interactions between learners and instructors. The study identifies that while AI systems can effectively support online learning by personalizing student experiences and automating routine tasks, there is a risk of reducing meaningful interactions between learners and instructors.	To mitigate this, the study suggests integrating AI tools that enhance, rather than replace, human interactions. It emphasizes the importance of designing AI systems that facilitate communication and engagement between students and educators.
[22], [23], [24], [25]	-AI in education may limit the development of students' critical thinking and creativity, as AI systems often provide predefined answers, reducing opportunities for independent problem-solving.	The balanced approach, where AI is used as a supplementary tool to support educators in fostering critical thinking and creativity among students, rather than replacing traditional teaching methods.
[35], [27], [28]	-A lack of comprehensive policies and knowledge sharing regarding the integration of AI in educational settings can lead to inconsistent implementation and potential ethical concerns.	Developing clear policies and frameworks to guide the ethical use of AI in education. Additionally, it advocates professional development programs to equip educators with the necessary skills to utilize AI technologies effectively.
[30], [40], [31]	-The digital divide among students and the preparedness of institutions to adopt new technologies.	Develop strategic plans that address data security, provide equal access to technological resources, and offer training programs to prepare both faculty and students for the effective use of AI tools.

Table 2 presents the types of data used in the reviewed studies for training AI-wit-models in support of the educational process, with a concise explanation of each type of data and its use. The table summarizes the different kinds of data that have been employed in the AI-for-education studies, from interaction data in intelligent tutoring systems to various facial expressions datasets for monitoring student engagement in online learning settings.

Table 2 Types of Data Used for Training AI Models in Education and Their Applications

Study	**Data Type**	**Description / Reason for Use**
[41]	Student Facial Images (FER Data)	Periodically captured images of students during online learning are used to extract facial expressions. The system is validated with standardized FER datasets (FER-2013, RAF-DB, CK+, KDEF) to monitor and evaluate emotional states for real time engagement assessment.
[42]	Benchmark FER Datasets and a Custom Learner Dataset	Standard benchmark datasets—FER-2013 (grayscale images), CK+ (lab-controlled color images), and RAF-DB (in-the wild colored images)—plus a proprietary dataset collected from online learners. These are used to train deep learning models (Inception V3, VGG19, ResNet 50) for accurate real time engagement detection.
[31]	Intelligent Tutoring System Interaction Data	Data such as clickstream records, time spent on tasks, correct/incorrect responses, and number of attempts collected from intelligent tutoring systems. This data helps identify student behavior patterns and informs adaptive learning strategies.

[36]	Detailed Interaction Data from Tutoring Systems	Data from repositories like PSLC DataShop—including problem-solving steps, time per step, and response accuracy—used to build predictive models that identify at risk students and assess learning strategies.
[37]	Adaptive Learning System Response Data	Student responses, question difficulty levels, and the number of attempts are used for knowledge tracing, allowing the system to predict future performance and tailor personalized learning paths.
[38]	Tutoring System Performance Data	Metrics such as the number of attempts, time spent on each attempt, and variations in problem-solving strategies are analyzed to detect “wheel spinning” behavior and design interventions.
[39]	Interaction Data from Educational Systems	Data collected on mouse movements, clicks, time spent on activities, and response accuracy, which are used to build user models for providing personalized feedback in exploratory learning environments.
[40]	MOOC Interaction Data	Data on video watching patterns, quiz performance, forum participation, and assignment submissions is clustered to identify subpopulations of learners, aiding in the design of targeted interventions to improve engagement and retention.
[43], [45]	Comprehensive FER Datasets Across Age Groups	A range of datasets covering adult (e.g., JAFFE, FER 2013, CK+, Radboud Faces Database, NVIE, AR Face, AFEW, AffectNet), children (e.g., LIRIS, DEFSS, NIMH ChEFS, Dartmouth, CAFE, EmoReact), and senior facial expressions (e.g., Tsinghua Facial Expression Database, Database for Emotional Interactions with Elderly, FACES). These support robust model training by capturing diverse expressions under various conditions.

Table 2 provides a comprehensive overview of the diverse data types used to train and evaluate AI models in educational settings. For instance, it depicts how specific facial expression datasets, namely FER-2013, RAF-DB, and others like CK+, KDEF, etc., are employed for real-time engagement assessment using extraction and analysis of student facial expressions. This is further improved through custom datasets directly obtained from online learners. The table also demonstrates how different interaction data with intelligent tutoring systems (e.g., clickstream data, the steps taken in solving a problem, and accuracy in response) are essential for discovering behavioral patterns for students for adaptive learning. Moreover, data collected from any MOOCs and adaptive learning systems will assist in predictive modeling about the patterns of watching videos and quizzes, among many other key engagement metrics, leading to personalized feedback. By merging different data sources in this way, researchers should be able to create AI models that are not just accurate for measuring a student level of engagement but also relevant to custom instructional intervention, which in turn should strive for improving learning gains and more efficient processes of education.

4. RELATED WORK COMPARISON

Compared to previous studies, our research builds upon existing findings by addressing the gaps identified in prior literature. While many studies have examined the technical capabilities of AI in education, fewer have investigated the alignment of AI-based educational tools with student engagement and learning effectiveness. Our study differentiates itself in the following ways:

- Focus on Transparency and Explainability: Unlike prior research that primarily discusses AI efficacy, our study explores the importance of explainable AI (XAI) in educational applications to ensure trust and acceptance among educators and students.
- Integration with Pedagogical Theories: Many existing studies have emphasized AI-driven automation without considering its alignment with established educational methodologies. Our research investigates how AI tools can be designed to complement traditional teaching approaches.
- Long-Term Impact Evaluation: Most previous studies focus on short-term AI implementation results. This research highlights the need for longitudinal studies that assess AI’s long-term effects on learning outcomes and student development.
- Addressing Bias and Fairness: While prior research has identified bias in AI decision-making, our study provides concrete recommendations on how to develop fair AI algorithms that promote inclusivity and equity in education.
- Bridging the Human-AI Interaction Gap: Unlike studies that treat AI as a standalone solution, this research emphasizes the integration of AI as a supportive tool that enhances human-led teaching rather than replacing it.

By considering these aspects, this study contributes to the growing body of literature by not only identifying challenges but also proposing practical solutions that ensure AI is implemented in a manner that is ethical, transparent, and effective for educational purposes.

5. DISCUSSION

This study highlights the significant role of artificial intelligence in enhancing educational environments, with technologies such as machine learning, deep learning, and natural language processing contributing to the development of personalized and effective teaching strategies. Although several previous studies have addressed the use of these technologies, our study underscores the gaps present in current applications and highlights how practical improvements can be achieved.

Through the literature review, key challenges in implementing AI in education were identified, such as issues related to privacy, algorithmic bias, and the misalignment of AI techniques with educational theories. We proposed solutions to address these challenges, including the development of more ethical and transparent systems, the creation of high-quality and diverse datasets to support models, and the integration of human-centered AI principles. However, the most significant contribution of this study lies in presenting new insights for readers by identifying ways to overcome these challenges and enhance the effectiveness of AI in educational processes. For example, the recommendations put forth, such as adopting Human-Centered AI approaches and establishing clear privacy and transparency policies, are crucial steps toward improving educational quality and achieving better outcomes for students.

Critique of the work lies in the fact that while practical solutions to these challenges are presented, there is still an urgent need for further research to expand these solutions and apply them in real-world settings. For instance, as emphasized in previous studies, the considerable gap between educational theories and AI applications remains a significant challenge. This gap could lead to unsatisfactory outcomes if efforts are not directed toward ensuring that technologies align with effective teaching methods.

Through this discussion, the study enhances the quality of the research by providing a deep critique of the challenges and future opportunities. It also paves the way for future work aimed at improving the integration of AI with educational theories to provide the best possible learning experience for students across various educational settings**.**

6. OPEN Research Issues

While this study offers valuable insights into the integration of AI in education, several open research issues remain. One key issue is the need for further development of AI models that can better account for diverse student learning styles and engagement patterns, ensuring that personalized learning systems are truly adaptive. Another significant challenge lies in improving the transparency and explainability of AI-driven decisions, particularly in educational contexts where the consequences of algorithmic decisions can greatly affect student outcomes. Additionally, long-term studies are needed to evaluate the sustained impact of AI applications on student performance and motivation, especially considering the rapid advancements in AI technologies.

Another area for future research involves addressing the ethical considerations of using AI in education, particularly in terms of privacy, data security, and the potential for bias. Developing standardized frameworks for implementing AI across diverse educational settings is also an area that requires more attention. Finally, exploring the role of human-centered AI, which integrates the psychological and social aspects of learning, is essential for creating more inclusive and effective AI systems.

These unresolved issues present an exciting opportunity for researchers to continue refining AI applications in education, ensuring they are both effective and ethically sound.

7. CONCLUSION

In conclusion, this research highlights the transformative potential of AI in education by demonstrating increased learning performance and engagement. AI systems provide personalized learning through adaptive tutoring, real-time performance tracking, and personalized feedback, allowing AI to lessen reliance on traditional resource-hogging forms of teaching. AI-related techniques in education, from machine learning to deep learning to NLP have improved administrative efficiency and teaching effectiveness. Still, there are unresolved concerns pertaining to data quality, algorithmic transparency, and ethical dilemmas like bias and respect for user privacy. These are the challenges that must be confronted in future navigations of this domain so that AI models are improved for monitoring student engagement and providing timely interventions in support of the education system, with technology being a supplement and not a substitute for the intrinsic human factor. It is essential for sustainable educational outcomes that the students' best interests be served by a balanced arrangement that combines advanced AI tools with traditional methods of teaching.

While this study provides a comprehensive review of AI applications in education, it also highlights the need for further research to bridge the gap between technological advancements and their pedagogical effectiveness. One key area for future exploration is the development of explainable AI models that offer greater transparency and

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accountability in decision-making processes, ensuring that students and educators can trust AI-driven recommendations.

Moreover, this research underscores the importance of addressing ethical concerns, particularly in mitigating biases within AI-driven educational tools. Future studies should focus on developing frameworks to ensure AI systems are designed and deployed in ways that promote inclusivity and do not reinforce existing educational disparities.

Ultimately, the findings of this paper contribute to the growing discourse on AI in education by not only summarizing existing advancements but also critically evaluating their limitations and proposing pathways for future improvements. By fostering a balanced integration of AI and human-led instruction, educational institutions can harness the full potential of AI while preserving the essential human elements of teaching and learning.

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