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Ethical Consideration in Implementing AI-based Tutoring Systems as Educational Technology Tool in Education: Balancing Efficiency with Privacy and Equity in the Teaching of Students

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Abstract

This article explores the major technological advancements in education and the ethical issues they raise. In this research, we use the systematic literature mapping method. The study follows the research methodology outlined by Kabudi, Pappas, and Olsen, with guidance from Petersen, Vakkalanka, and Kuzniarz. The methodology applied in both studies is as follows: (i) search and selection, (ii) data extraction, (iii) classification and analysis, and (iv) evaluation of validity. The PRISMA approach, or Preferred Reporting Items for Systematic Reviews and Meta-Analyses, was used as a framework for the search and selection phase. Key findings reveal that AI can automate grading and provide personalized feedback to students, while also reducing cheating. It also helps in predictive analytics by predicting learning outcomes and identifying at-risk students. AI also evaluates non-cognitive traits like emotional states and collaborative skills. However, the study also highlights ethical issues in AI-based assessments, such as inclusivity, fairness, accountability, accuracy, explanation, auditability, security, privacy, autonomy, consent, and sustainability. The research identifies five key thematic areas: AI system design, AI-driven assessment rollout, data stewardship, assessment administration, and grading and evaluation. The study concludes that while AI presents transformative opportunities for educational assessments, it also introduces complex ethical challenges that must be carefully managed.

A. Introduction

The terms "AI" in education, "adaptive learning technology," "learning analytics," "educational data mining," "educational data science," "teaching analytics," "data-driven decision-making in education," and "big data in education" are frequently used broadly and interchangeably depending on the context in papers pertaining to educational technology (Romero & Ventura, 2020).

It's helpful to remember that "intelligence" in AI is a spectrum. AI can be mapped into Bloom's taxonomy of learning, according to Chassang et al. (2021), where "Crystallized Intelligence" refers to lower order thinking skills and "Fluid Intelligence" to higher order thinking skills. While the latter involves a higher level of intelligence abstraction, with "the ability to solve new problems, use logics in new situations, and identify patterns without necessarily having the prior experience of similar information or problems," the former primarily consists of supervised learning (or target-based prediction) with "encoding capacity, middle-long term memory, and ability to access memorized data in a logical way."

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Depending on its particular use cases, Artificial intelligence in education (AIED) is a superset that includes terminology like learning analytics or educational data mining (Lim et al., 2023). The technological difficulties of creating and implementing data mining methods in education are comparatively the main emphasis of educational data mining. One use of AI known as Crystallized Intelligence is the use of educational data mining, which entails creating a natural language processing algorithm to analyze various word embeddings based on text similarity in open-ended quiz replies. Learning analytics, on the other hand, is more concerned with the educational difficulties of making decisions based on data by using predictive models. For example, learning analytics using neural networks' capacity for abstract thinking.

AI-based tutoring systems are revolutionizing education in Nigeria by providing personalized learning experiences and automating administrative tasks (Eyikorogha & Chigozie, 2024). However, these systems raise significant ethical concerns, particularly in the context of Nigeria, where educational disparities and data privacy concerns persist (Ajiga et al., 2024). Key privacy concerns include data security, consent and transparency, and data minimization. Equity and access issues arise from AI-based tutoring, such as the digital divide and bias in AI models. To address these challenges, stakeholders should adopt strategies such as strengthening data protection laws, promoting digital literacy, bias mitigation, and community engagement.

To address these challenges, Nigeria must enhance its data protection regulations, promote digital literacy programs, test AI systems for bias, and involve educators, parents, and students in the design and implementation of AI tutoring systems. By fostering collaborative efforts between policymakers, educators, and technology developers, Nigeria can harness the benefits of AI while safeguarding students' rights and promoting inclusive education for all

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Equity and access issues arise from AI-based tutoring, such as the digital divide and bias in AI models (Sato et al., 2024). To address these challenges, stakeholders should adopt strategies such as strengthening data protection laws, promoting digital literacy, bias mitigation, and community engagement.

African nations must enhance their data protection regulations to address the unique risks posed by AI in education. Government and private sector initiatives should focus on expanding digital infrastructure and literacy programs. Developers should actively test AI systems for bias and involve diverse datasets in training models. Community engagement ensures that educators, parents, and students are involved in the design and implementation of AI tutoring systems.

In conclusion, AI-based tutoring holds immense potential to revolutionize education in Africa, but ethical considerations around privacy and equity must be addressed. By fostering collaborative efforts between policymakers, educators, and technology developers, Africa can harness the benefits of AI while safeguarding students' rights and promoting inclusive education for all.

Artificial Intelligence (AI) is revolutionizing the educational landscape by providing personalized learning experiences, automating administrative tasks, and enhancing teaching methodologies. AI-based tutoring systems hold significant potential to improve learning outcomes by tailoring content to individual students' needs and learning paces (Admane et al., 2024). However, the integration of AI in education raises important ethical considerations that must be addressed to ensure that efficiency does not compromise privacy and equity.

Privacy concerns arise from the vast amounts of data collected by AI tutoring systems, including learning habits, preferences, and performance (Baig et al., 2024). Unauthorized access, data breaches, and misuse of personal information can undermine trust in these systems. Educational institutions must adopt stringent data protection measures, including encryption, anonymization, and compliance with global data privacy regulations such as the GDPR. Transparency in data usage is critical, and students and their guardians should be informed about the type of data being collected, how it is used, and who has access to it.

Equity and accessibility are also crucial aspects of AI integration in education. Access to AI tools may be limited by factors such as socioeconomic status, internet connectivity, and technological infrastructure, widening the digital divide. To promote equity, educational institutions should ensure that AI tools are accessible to all students, regardless of their background. Addressing bias requires diverse and representative datasets, regular audits, and continuous refinement of algorithms.

Human oversight and accountability are essential for interpreting results, providing emotional support, and addressing complex student needs. Clear accountability frameworks should delineate the responsibilities of AI developers, educators, and institutions, ensuring that ethical lapses can be promptly addressed (Fu & Weng, 2024).

In order to provide a thorough framework for the responsible use of these potent tools in influencing the future of learning, this article explores the major technological advancements in education and the ethical issues they raise. As we traverse this quickly changing landscape, it is imperative that we strike a balance between the enormous potential of educational technology and a dedication to equity, privacy, and ethical practice.

B. Research Methods

In this research, we utilize a systematic literature mapping approach. The methodology follows that outlined by Kabudi et al. (2021), building on the guidelines from Petersen et al. (2015). The methodology applied in both studies includes: (i) search and selection, (ii) data extraction, (iii) classification and analysis, and (iv) validity evaluation.

The PRISMA approach, or Preferred Reporting Items for Systematic Reviews and Meta-Analyses, was used as a guideline for the search and selection process. In line with the PRISMA-P checklist recommendations, we outline the eligibility criteria, data sources, search protocol, research records, data items, and data synthesis in the following sections.

To organize the information, NVivo11, EndNote X9, and Excel spreadsheets were employed. Further data extraction, visualization, and machine learning methods are explained in the subsequent sections.

Search and Selection

Given that AIED researchers come from diverse disciplines and publish in various sources, we conducted a literature search using Scopus, a comprehensive database covering 240 disciplines, with over 87 million publications 1.8 billion cited references, 17 million author profiles, 94,000 affiliation sources, and 7,000 publishers. A more thorough systematic literature mapping study is implied by the fact that each paper indexed on Scopus typically has 10% to 15% more citations than similar databases, making it ideal for extensive systematic mapping.

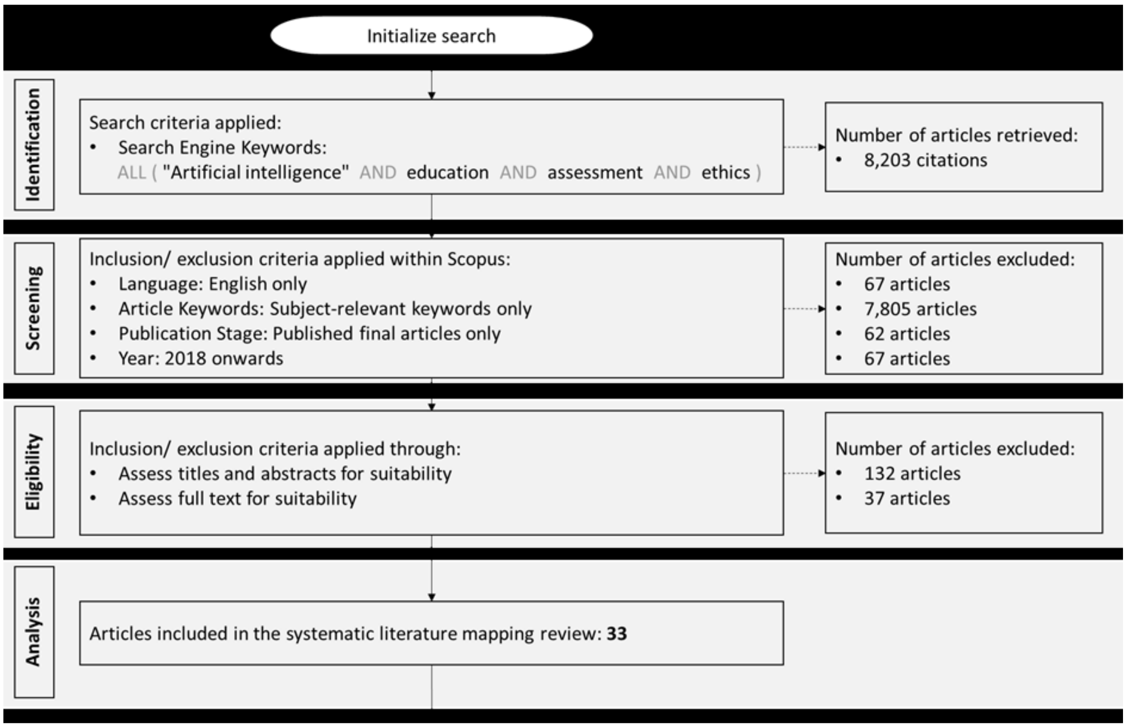

Figure 1. PRISMA - The systematic mapping process

The initial PRISMA stage, the identification phase, used the Scopus search engine to identify relevant papers. The search term used was: ALL ("*Artificial intelligence" AND education AND assessment AND ethics*), yielding 8,203 results.

The second PRISMA stage, the screening phase, excluded irrelevant papers, reducing the count to 202. Inclusion criteria were:

- Language: Only English-language articles were included, eliminating 67 papers.
- Keywords: Only articles with subject-relevant keywords were included, removing 7,805 papers.
- Publication Stage: Only peer-reviewed, final articles published in scientific venues were included, removing 62 papers.
- Publication Year: Only articles from 2018 onwards were included, omitting 67 papers.

The third PRISMA stage, eligibility, involved reviewing titles, abstracts, and full papers to identify relevant articles, resulting in 33 papers. Inclusion criteria applied:

- Titles and abstracts were assessed for relevance, eliminating 132 papers.
- Full papers were reviewed for suitability, with 37 papers excluded.

A summary of the PRISMA approach is shown in Fig. 1.

Data Extraction

Scopus, as a citation engine, provides structured and well-tagged data, offering metadata for analysis, such as authors, document titles, affiliations, publication year, citation counts, document types, keywords, and DOIs.

The final set of 33 papers was analyzed to answer the study's research questions. Data extracted from Scopus included citation information, bibliographical data, abstracts, keywords, and references.

Classification and Analysis

The study utilized Tableau Desktop Professional version 2021.1.20 for exploratory data analysis to address Research Question 1 (RQ1). Tableau facilitated the conversion of complex computations into meaningful visualizations.

Using data from Scopus, the research employed the CorTexT platform for text parsing, topic modeling, and network mapping to identify major themes in the corpus of Author and Indexed Keywords. This helped recognize patterns using unsupervised machine learning techniques for text mining.

The topic modeling process, using the Python library pyLDAvis, employed the Latent Dirichlet Allocation method to visualize keyword distributions and topics. This approach probabilistically assigned topics to documents, displayed in a 2D visualization based on a multi-dimensional scaling algorithm.

Network analysis further visualized keyword themes in clusters, with the Louvain hierarchical community detection algorithm applied to measure optimal linkage densities. This method works efficiently for large networks.

The first pass of topic modeling and network analysis identified key sub-themes in AI application areas and ethical issues. These sub-themes were used to categorize papers by (i) AI application areas in assessments (e.g., personalized feedback) and (ii) ethical issues (e.g., fairness, explainability), addressing Research Questions 2 and 3.

The study also analyzed mitigation and intervention strategies for each ethical issue, such as using data sanitization to reduce discriminatory risks. A second pass of topic modeling and network analysis guided the identification of major research themes for Research Question 4.

Evaluation of Validity

To ensure the robustness of the systematic mapping approach, several validity types were considered: (i) descriptive validity, (ii) interpretive validity, (iii) theoretical validity, and (iv) generalizability (Petersen et al.,2015). Thorough reporting of the methodology, including validity evaluation, supports repeatability.

- Descriptive Validity: This ensures objective and accurate observations. A data extraction and coding spreadsheet was designed to maintain objectivity and accuracy.
- Interpretive Validity: This addresses the validity of conclusions drawn from the data. To minimize

researcher bias, no papers authored by the research team were included.

- Theoretical Validity: This checks if the identified themes align with real-world patterns. Scopus' integration with major publishers helped reduce the likelihood of missing key information, and careful paper curation ensured the literature was accurate and current. An independent reviewer with relevant expertise assessed the methodology and data extraction.
- Generalizability: This refers to the external validity (the ability to generalize results) and internal validity (the causal relationship between AI applications in assessments and ethical issues). Although generalizability may be influenced by domain, culture, and sample size, future research could address these concerns (Khan et al., 2024).

Limitations

We acknowledge that there are other databases available, even if Scopus is a strong one for mapping and surveying specialized scientific fields with digital records for peer-reviewed literature (Fahimnia et al., 2015). Other legitimate options include, but are not limited to, Web of Science, ACM, IEEE Xplore, EBSCO Host, Wiley, SAGE Journals, and Taylor and Francis. Among these databases, Campedelli (2021) makes the case that there may be more than 50% to 60% overlap between the publication titles in both databases; hence, it may be beneficial to include both databases. However, Scopus' informative tagging of all papers by professional indexers using Indexed Keywords existed more frequently and offered a richer pool of content for each item, especially for textual mining purposes, than Web of Science's Keyword Plus. This discriminant feature, in turn, supported the selection of Scopus. This should be adequate as an initial evaluation of this topic. To offer a thorough scan of this landscape, it will be helpful to think about integrating Web of Science and/or other pertinent databases for follow-up study.

Furthermore, the study did not examine the potential impact of thematic diversity within AI applications. Future research could explore how variations in thematic diversity affect AI assessments, including operationalization and ethical considerations. Applying economic valuation methods like those from Klinger et al. (2020) and Weitzman (1993) may provide insights into the value and sustainability of thematic diversity in AI-related research.

Second, no presumptions regarding the inherent worth of theme diversity were made in this chapter. This work aims to serve as a crucial foundation for future research by using unsupervised machine learning approaches to find latent ideas contained in the body of existing literature. The scope of this study does not include the investigation of potential inhibited or dysfunctional states within this thematic variety, which are likely caused by academic or technological stasis, or the absence of infrastructure or skills leading to resistance to state-of-the-art adoption. Future studies could benefit from measuring the importance of this thematic diversity in terms of (i) how it can be operationalized as a separate assessment pipeline component and (ii) how much ethics or the lack thereof affect the assessment pipeline component separately or in combination. Applying Weitzman's (1993) economic valuation of ecological diversity which considers the cost-benefit analysis of conserving diversity and the threshold at which the archetypal research theme becomes unsustainable may be helpful, as suggested by Klinger et al. (2020).

C. Results and Discussion

This section presents the findings based on an analytical investigation of selected published primary papers identified as relevant to the study.

Research Question (RQ) 1: Where do the studies that discuss ethical issues relating to AI-based assessments arise from?

To address RQ1, research undertook exploratory data analyses to explore where the studies discussing ethical issues relating to AI-based assessments arise from.

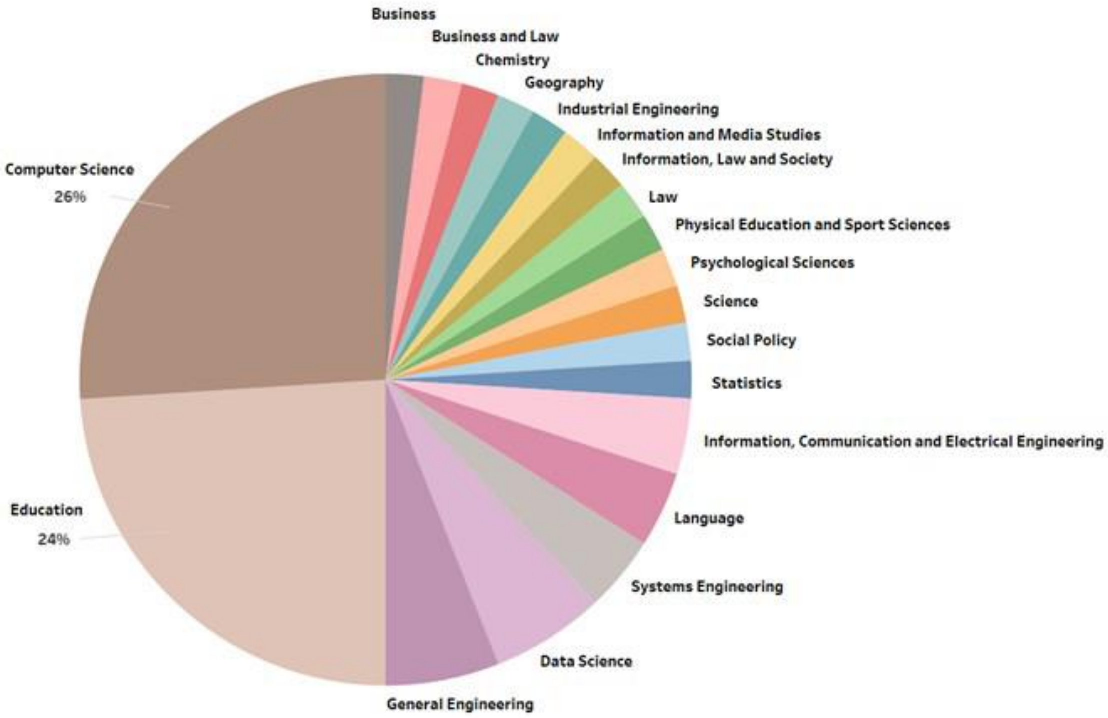

Figure 2. Breakdown of disciplines tied to authors' affiliated department

It was observed in Fig. 2 that the publications came from scholars in a variety of areas by looking at the departments with which the authors were linked. The departments of education and computer science account for around half of the researchers, with computer science coming in second. The remaining amount came from 18 different fields, which ranged from hard applied disciplines like engineering to soft, pure disciplines like language. This implies that research on AI-integrated evaluations and ethics comes from a wide range of disciplines rather than just education departments.

The study explores the use of AI in educational assessments, focusing on its applications in assessment construction, grading, and feedback. Key findings reveal that AI can automate grading and provide personalized feedback to students, while also reducing cheating. It also helps in predictive analytics by predicting learning outcomes and identifying at-risk students. AI also evaluates non-cognitive traits like emotional states and collaborative skills. However, the study also highlights ethical issues in AI-based assessments, such as inclusivity, fairness, accountability, accuracy, explanation, auditability, security, privacy, autonomy, consent, and sustainability. The research identifies five key thematic areas: AI system design, AI-driven assessment rollout, data stewardship, assessment administration, and grading and evaluation. The authors suggest expanding AI ethics frameworks, improving transparency, and increasing cross-disciplinary collaboration to ensure ethical AI integration in education. This study provides valuable insights into the evolving role of AI in educational assessments and emphasizes the need for ethical concerns to foster fair, transparent, and inclusive AI-driven educational practices.

D. Conclusion

The study concludes that while AI presents transformative opportunities for educational assessments, it also introduces complex ethical challenges that must be carefully managed. By systematically mapping the literature, the research highlights key ethical concerns such as fairness, inclusivity, accountability, and transparency, which are critical to ensuring that AI-driven assessments are equitable and effective.

The authors emphasize the importance of developing robust frameworks to guide the ethical deployment of AI in education, advocating for greater collaboration across disciplines and the involvement of diverse stakeholders. They recommend continuous auditing, clearer regulations, and stronger governance to mitigate risks and ensure AI technologies align with educational values and societal norms.

Ultimately, the study calls for a balanced approach that harnesses AI's potential while safeguarding the rights and well-being of learners, promoting a more just and inclusive educational landscape.

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