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Examining AI Predictions of Academic Self-Efficacy and Their Influence on Teaching Strategies, Curriculum Design, and Student Support Systems

By

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Abstract
In recent years, artificial intelligence (AI) has shifted from an emerging technology into a fundamental pillar across multiple sectors, especially in education. The integration of AI in education holds significant promise for the improvement of educational quality, the advancement of teaching methodologies, and the refinement of assessment strategies, all while training students for their prospective careers. Academic self-efficacy (ASE), is a student's belief in their capability to perform academic tasks. ASE has been widely recognized as a key determinant of positive learning outcomes and motivation. There are growing opportunities to use data analytics and machine learning algorithms to predict student outcomes and behaviors. One promising application lies in predicting academic self-efficacy based on data from learner behavior and performance. This review synthesizes key literature on how AI-generated insights into ASE can inform teaching strategies, curriculum designs and student support systems.

Key words: self-efficacy, artificial intelligence

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Introduction

Academic self-efficacy (ASE), defined as a student's belief in their capacity to execute academic activities (Bandura, 1997), is widely acknowledged as a crucial factor influencing learning outcomes and motivation. The emergence of artificial intelligence (AI) in education presents an increasing opportunity to utilize data analytics and machine learning algorithms for predicting student outcomes and behaviors. A notable use is forecasting academic self-efficacy utilizing behavioral and performance data. As AI technologies like natural language processing (NLP) and learning analytics advance, higher education institutions are progressively utilising AI-generated outputs (e.g., dashboards, feedback systems, and personalized learning environments) to assess, improve, and inform ASE. Comprehending these forecasts might provide educators with practical insights to customize instructional methodologies, reformulate curriculum, and enhance student support systems. This study consolidates essential material on how AI-generated insights about ASE might enhance teaching strategies, curriculum designs, and student support systems.

Problem Statement

Although AI applications in education have experienced considerable expansion, the majority of implementations prioritize forecasting academic achievement (Nagy et al, 2024; A. Chen et al, 2025) above fundamental psychological characteristics such as self-efficacy. Research on the practical application of AI-predicted self-efficacy ratings by educators to improve teaching methodologies, customize curricula, and create adaptive student support systems is limited. The potential of AI in such circumstances remains largely unexploited without integration into pedagogical and institutional frameworks. Self-efficacy is a vital factor influencing academic performance, motivation, and persistence; yet, its correct measurement and enhancement pose challenges in educational environments (*Experiential High School Career Education, Self-Efficacy, and Motivation on JSTOR, n.d.*). Traditional approaches, including surveys and self-reports, are constrained by subjectivity, delayed responses, and possible biases (Basic Elements of Survey Research in Education, n.d.).

Kenya is presently implementing a new curriculum, the Competency Based Curriculum (CBC), which contains several ambiguities. One of the problems of CBC is determining the diverse pathways for learners who choose the STEM and Arts tracks, (Micheni, (2024). This is a worry as the school-based assessment, which constitutes a component of the summative evaluation at the conclusion of junior secondary school, may not accurately represent the students' true achievements by the end of the course (Looney, 2011). The lack of coordination in the marking guide results in subjective outcomes based on the teacher's assessment. This may yield deceptive outcomes. The study thus examines the place of Artificial Intelligence (AI) in offering a solution to these difficulties by examining learning behavior, performance metrics, and psychological variables to forecast the self-efficacy levels of students transitioning to senior schools.

Significance of the Study

This research bridges the gap between AI analytics and practical educational interventions. It aims to demonstrate how data-driven predictions can be translated into meaningful changes in pedagogy and student support services. Institutions implementing such frameworks may experience improvements in student engagement, retention, and academic achievement, especially for students at risk due to low self-efficacy. It may also provide insights that could guide future research endeavors besides advocating for evidence-based transformative and innovative teaching practices to enrich education through effective utilization of artificial intelligence.

Objectives

This study was guided by the following objectives:

i. To explore the use of AI-generated predictions of academic self-efficacy role in transforming teaching and support services in higher education institutions
ii. To Assess the ethical and practical considerations involved in using AI to analyze student self-efficacy.

Research Questions

To achieve its objectives, the study sought to answer the following questions:

i. How can AI-generated predictions of academic self-efficacy inform practice in higher education institutions?
ii. What ethical and practical considerations are involved in using AI to analyze student self-efficacy?

Literature Review

Bandura (1997) recognized academic self-efficacy as a significant determinant of educational achievement and perseverance. Various research (Pajares, 2002; Schunk & DiBenedetto, 2016) have corroborated this, demonstrating its impact on motivation, goal formulation, and resilience. Simultaneously, artificial intelligence in education has been employed to forecast outcomes like academic performance (Kizilcec & Halawa, 2015), attrition rates (Lakkaraju et al., 2015), and levels of engagement (Woolf et al., 2013). AI has the potential to revolutionize the instruction and acquisition of curriculum disciplines, particularly through its capacity to replicate scientific investigations and offer virtual laboratory experiences to students. This allows students to hone and enhance their scientific skills in a secure and regulated environment, thereby reducing costs and providing new avenues for investigating scientific issues that may be impractical in conventional laboratory settings (Wahyono et al., 2019). According to the analogy that: “What I hear, I forget; what I see, I remember; and what I do, I understand,” learners are naturally driven by virtual laboratory technology, which enhances their self-efficacy.

AI allows instructors to abandon regular teaching methods by offering students customized and engaging learning experiences. Zhai et al. (2021) assert that AI-powered algorithms can transcend mere recommendations and evaluations to do in-depth studies of students' learning habits, facilitating highly personalized learning experiences. Additionally, students can gain from prompt feedback and personalized learning trajectories that allow them to rectify misunderstandings of topics (Mavroudi et al., 2018). Furthermore, AI can assist educators in tracking and monitoring students' progress more efficiently, facilitating targeted interventions and support as necessary.

AI facilitates the creation of dynamic and immersive educational environments, enhancing engagement and accessibility for learners with varied styles and requirements. Students in these situations are likely to possess elevated academic self-efficacy. Limited research has utilized machine learning to forecast self-efficacy explicitly. Nonetheless, research by Thai-Nghe et al. (2011) and Koedinger et al. (2015) demonstrates the viability of forecasting cognitive-affective moods from educational data. A research gap exists in correlating these predictions with implementable modifications in pedagogy and curriculum design.

Academic Self-Efficacy: Theoretical Foundations

Bandura's social cognitive theory (Bandura, 2001) posits that self-efficacy, defined as perceived skills for learning or executing tasks at specific levels, is a crucial cognitive factor affecting motivation and engagement (Schunk & DiBenedetto, 2022). Self-efficacy, a fundamental component of social cognitive theory, is a significant variable influencing students' motivation and learning (Van Dinther et al., 2011). Their research indicated that educational programs can enhance students' self-efficacy, with those grounded in social cognitive theory demonstrating particular efficacy in fostering self-efficacy acquisition among students. Self-efficacy, a fundamental component of social cognitive theory, is a crucial variable in student learning, as it influences students' motivation and educational outcomes. Extensive research indicates that self-efficacy influences students' performance and learning behaviors, including task selection, effort, perseverance, and outcomes (Van Dinther et al., 2011).

Bandura posits that self-efficacy beliefs are fundamental to human functioning (Bandura, 2012). Individuals must not only possess the necessary information and abilities to execute a task but also have the confidence to successfully conduct the required behaviors in both ordinary and demanding settings. Effective functioning necessitates skills and efficacy beliefs for their proper execution of two interrelated components that evolve concurrently as persons mature and acquire knowledge.

Furthermore, these two elements of effective human functioning interact reciprocally, a concept termed 'reciprocal causation,' wherein the performance of one element is partially contingent upon the performance of the other (Artino Jr. 2012). Bandura's Social Cognitive Theory offers a fundamental paradigm for comprehending academic self-efficacy. It asserts that self-efficacy is affected by mastery experiences, vicarious experiences, verbal persuasion, and physiological conditions. AI-enhanced technologies, such intelligent tutoring systems and adaptive learning platforms, engage with these sources in innovative manners. Academic self-efficacy is associated with tenacity, academic achievement, intrinsic motivation, and resilience (Zimmerman, 2000). In digital learning environments, ASE is essential for student engagement and achievement, particularly in self-regulated and remote settings.

Indicators for self-efficacy

A study by Coutinho and Neuman (2008) employed structural equation modelling to evaluate a model that integrates accomplishment goal orientation, learning style, self-efficacy, and metacognition into a cohesive framework that elucidates and forecasts variations in performance. Self-efficacy emerged as the most significant predictor of performance. Self-efficacious learners demonstrate increased effort, persist longer with challenging activities, and exhibit resilience by learning from unfavorable learning experiences. Students possessing high self-efficacy perceive problems as challenges, establish goals and demonstrate commitment to them (Schunk & Mullen, 2012). Such students ascribe failures to insufficient effort, unacquired skills, and limited knowledge. They therefore intensify their attempts to surmount the setbacks and achieve set goals (Han, 2021). Self-efficacy, akin to many elements of socio-emotional learning, serves as both a facilitator of academic success and a product of educational experiences.

Research indicates that interventions aimed at enhancing students' self-efficacy beliefs can positively affect academic performance and subsequent activities in life (Pajares, 2002). Self-efficacy is shaped by four key kinds of information: performance achievements, vicarious experiences, verbal encouragement, and physiological feedback. Additional drivers of self-efficacy include internal human characteristics and external environmental influences. The extent of improvement in self-efficacy is partially influenced by the variability and controllability of its causes (Van Der Bijl & Shortridge-Baggett, 2001).

Assessment of self-efficacy

The assessment of self-efficacy pertains to three dimensions: quantity, strength, and generality. Self-efficacy must be assessed through specific evaluations of competence that can differ across various activity domains, levels of task demand within a single domain, and situational contexts (Van Der Bijl & Shortridge-Baggett, 2001). General self-efficacy is an individual's assessment of their capability to execute activities in many circumstances (G. Chen et al., 2001). This is generally evaluated by examining confidence levels in task execution and the ability to complete a certain task. Numerous underperforming students exhibit aversion to academics stemming from diminished self-efficacy. To counteract low self-efficacy, educators must emphasize the cultivation of high self-efficacy by connecting new tasks to recent successes, employing innovative pedagogical strategies, reinforcing effort and perseverance, facilitating peer modelling, and assisting learners in establishing attainable personal goals (Margolis & McCabe, 2004).

Artificial Intelligence and Academic Self-Efficacy

Recent advancements have resulted in the growth of AI-driven educational systems, such as Intelligent Tutoring Systems (ITS). These facilitate individualized teaching by offering prompt feedback, customized training, and performance analysis (Baig, & Minsky, 2024). Learning analytics and predictive models: AI-driven analytics can monitor student engagement and performance, analyze student data, forecast learning outcomes, and discern behavioral patterns to deduce ASE levels (Siemens & Long, 2011). Machine learning models utilising historical data can forecast at-risk students based on low ASE indicators (Dede et al., 2018). Natural Language Processing and Sentiment Analysis: NLP methodologies utilized on student essays, forum contributions, or reflections can disclose degrees of confidence, motivation, and emotional tone (Baker & Inventado, 2014). AI systems can produce adaptive ASE profiles that progress alongside students' learning paths.

The role of AI in predicting self-efficacy for learners

A study conducted by Rodríguez-Ruiz et al., (2025) used logistic regression analyses and found out that self-control and self-efficacy correlated with the utilisation of artificial intelligence for addressing daily uncertainties, stemming from the necessity of interaction and the completion of academic work on behalf of the student.

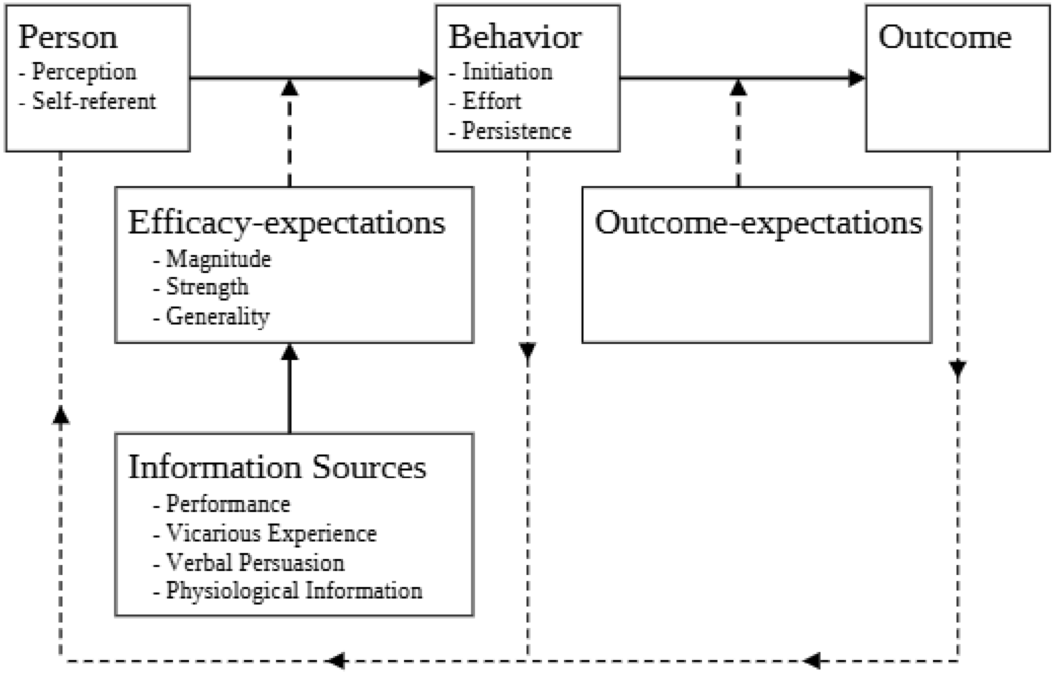

Figure 1: Self-efficacy model (Shortridge-Baggett & van der Bijl, 1996)

Informing and Revolutionizing Teaching Practices

The utilisation of AI has enhanced pedagogical methods in educational institutions. Numerous domains in education have been positively influenced by artificial intelligence. Areas include: Personalized Feedback: AI-generated ASE profiles can assist instructors in customizing feedback that enhances students' confidence and addresses learning deficiencies (Roll & Wylie, 2016). Real-time dashboards showcasing ASE indicators facilitate formative assessment and adaptive instruction; Inclusive and Differentiated Instruction: Educators can leverage AI insights to identify diverse learning requirements and apply differentiated strategies to accommodate varying ASE levels (Luckin et al., 2016); Professional Development: Faculty training initiatives are integrating AI literacy, empowering instructors to analyze ASE-related data and enact data-informed pedagogical transformations (Holmes et al., 2019).

Transforming Curricular Designs

Data-Informed Curriculum Mapping: AI systems identify areas in the curriculum where students commonly experience low self-efficacy, enabling curriculum designers to integrate scaffolded support (Kizilcec et al., 2020). Learning analytics dashboards can guide redesigns to emphasize skills and concepts that promote confidence-building. Adaptive Learning Pathways: Curricula can be dynamically adapted based on AI assessments of ASE, enabling personalized pathways that increase mastery experiences (Pardo et al., 2019). Reflective and Metacognitive Components: AI-informed curriculum design increasingly integrates reflective journals and self-assessment prompts that bolster ASE through structured self-awareness (Winne & Hadwin, 2013).

Enhancing Support Systems

AI-driven early warning systems can identify deteriorating ASE patterns, prompting either automated or human actions (Arnold & Pistilli, 2012). Virtual agents, such as chatbots, can offer motivational support and goal-setting aid customized to students' ASE levels. Moreover, advisers can utilize AI-enhanced ASE reports to gain insights into student challenges and offer tailored support (Ifenthaler & Yau, 2020). Consequently, they can offer academic advice and therapy AI technologies enable intelligent clustering for peer learning by pairing students with comparable ASE characteristics to promote reciprocal assistance (Rosé et al., 2019). Thus, AI functions as a peer support and collaboration instrument, enhancing ASE for learners.

Ethical and Practical Considerations in Using AI

Artificial intelligence in education is permanent. Consequently, significant ethical concerns must be addressed, particularly when incorporating AI into the classroom. Burton et al. (2017) and Cathrin and Wakandaru (2023) emphasized the necessity of character education. Kiendae and Kora (2022) contend that the incorporation of ethical courses in academic training and the capacity building of AI development stakeholders can promote the integration of ethical ideals and the advancement of responsible AI. The absence of critical reflection on the pedagogical and ethical ramifications, together with the potential risks of deploying AI technologies in education, necessitates the establishment of a complete ethical framework, as noted by Bozkurt et al. (2021) and Adams et al. (2022). The ethical implications of AI in education appear to encompass not only technical concerns but also wider societal impacts, including privacy protection and social justice (Hermansyah et al., 2023).

Robust controls are necessary for student data privacy, algorithmic bias, and transparency in AI-generated ASE assessments. Specific ethical considerations must be acknowledged, including informed permission, data anonymization, and Institutional Review Board (IRB) approval. Privacy concerns regarding the acquisition of student data from online learning platforms and behavioral patterns present substantial challenges, especially if students are uninformed that their data is utilized for psychological inference. This necessitates prompt disclosure to all parties, including learners. Moreover, informed consent necessitates transparent communication to students regarding the data collected, its intended use, and their opportunity to decline participation. The concern of data security is prominently raised in discussions around digital learning. The storage and processing of sensitive data must adhere to institutional norms and legal regulations to avert unauthorized access or misuse.

Predictive labels and stigmatization may occur when students perceived as possessing low self-efficacy are handled differently by instructors, either intentionally or unconsciously, resulting in self-fulfilling prophecies or stigmatization. Additional complications emerge when the dichotomy of autonomy versus automation is addressed. This may result from over dependence on AI recommendations, thereby undermining teacher autonomy and diminishing nuanced, human-centered decision-making in education and support. This may influence instructor readiness, significantly impacting the effective utilisation of AI-generated ASE data. Consequently, institutions must guarantee that AI selections are transparent and responsible; students and educators should comprehend the basis of forecasts and have the ability to challenge them if required.

Recommendations for Ethical Implementation

To mitigate the persistent ethical dilemmas associated with the utilisation of AI and other digital instruments in forecasting ASE, the subsequent recommendations may prove beneficial:

I. Employ varied and inclusive datasets during model training.
II. Utilize explainable AI (XAI) methodologies to enhance transparency.
III. Form oversight committees to conduct frequent audits of AI systems for equity and efficacy.
IV. Establish ongoing feedback mechanisms with students and teachers to ethically and collaboratively enhance predictive tools.
V. Student Agency: Caution is necessary to prevent excessive dependence on AI, since it may compromise student autonomy and intrinsic motivation.

Potential Biases in AI Models

Various forms of artificial intelligence (AI) applications are being deployed and used in many healthcare systems. As the use of these applications increases, we are learning the failures of these models and how they can perpetuate bias. With these new lessons, we need to prioritize bias evaluation and mitigation (Gichoya et al., n.d.). Efforts to mitigate these biases are challenging due to lack of a unified definition of bias; focus on a statistical definition of bias and a technocentric definition of bias. The following biases are bound to arise while using AI in teaching and learning:

i. Data Bias: AI models trained on historical data may inherit systemic biases related to gender, ethnicity, socio-economic status, or disability. This could result in unfair self-efficacy predictions that disadvantage certain student groups.
ii. Systemic biases in Algorithms and data: Certain modeling techniques may overfit or generalize poorly, leading to skewed outcomes for minority populations (Barocas et al., 2019) and perpetuation of inequities making it necessary to address these biases effectively (Adam's et.al., 2022)
iii. Representation Gaps: Underrepresented groups in training datasets may lead to inaccurate predictions for those populations, reinforcing educational inequalities

Future Directions

The utilisation of big data and artificial intelligence in education has progressed substantially. The ease of data collecting in educational technologies, along with computer methods, has rendered the analysis of huge data feasible. Trends are progressing beyond proof-of-concept demonstrations and uses of approaches, leading to significant adoption in several educational domains. The primary domains of big data and AI pertain to evaluation, personalized learning, and targeted education (Luan et al., 2020).

Machine learning, a subset of AI, concentrates on developing computer systems capable of autonomously learning from and adapting to data without explicit programming. These algorithms can yield novel insights, predictions, and solutions tailored to the specific needs and circumstances of individuals (Jordan & Mitchell, 2015). Two primary avenues for utilising AI to improve educational efficiency have been identified: the deployment of generative AI (which encompasses the creation of texts, plans, annotations, presentations, and images) and predictive AI (which focusses on the automation of educational processes)

(Tymoshenko et al., 2024). Future developments in AIED include: the integration of generative AI in ASE scaffolding via personalized learning dialogues and writing assistance; the creation of multimodal ASE indicators that amalgamate text, video, and behavioral data for comprehensive assessments; and the design of adaptive learning ecosystems that react in real time to changes in ASE, directing both learners and educators.

Conclusion

AI-generated insights into academic self-efficacy offer transformative potential for higher education. By enabling more responsive, personalized, and effective teaching practices, curricula, and support systems, these technologies can enhance both student success and institutional effectiveness. However, to realize this potential, thoughtful implementation and ethical oversight are essential.

Recommendations

The study made the following recommendations, based on its objectives, findings and conclusion

(i) There should be more empirical studies on AI-generated insights and their influence on students' academic self-efficacy

(ii) In order to realize AI potential in enabling more responsive , personalized and effective teaching practices, curricula and support systems, there is need for thoughtful implementation, collaboration and ethical oversight.

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