CHALLENGES AND RISKS OF IMPLEMENTING AI IN HIGHER EDUCATION

Examining the Complexities and Risks of AI in Higher Education: A Focus on Bias and Its Impact on Student Outcomes

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INTRODUCTION

In a 2021 EDUCAUSE QuickPoll involving 195 IT leaders from U.S. higher education institutions, a growing reliance on AI in education was evident, with 60% using it for plagiarism detection and 42% for online proctoring, accelerated by the shift to online learning during the pandemic. Chatbots were employed by 36% of institutions for handling student queries.

Despite the increasing use of AI, many institutions face significant challenges in fully integrating it. Two-thirds reported infrastructural limitations, with 72% struggling with data management, 71% with technical expertise, and 67% with budget constraints. Ethical concerns are also prominent, with 68% wary of moral implications and 67% worried about biases in algorithms potentially disadvantaging minority students.

Our article aims to offer a comprehensive examination of the complex issues surrounding AI in higher education settings. We will explore the potential risks, particularly in educational tools and systems, where biases can have significant consequences on students' academic and career trajectories.

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DATA SOURCE AND SAMPLE STRUCTURE

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Despite developers' best intentions, AI systems can produce unintended and sometimes harmful consequences. Relying on outdated or narrowly-focused data can skew results, like AI models tailored to students from a particular region or time being ineffective elsewhere. Moreover, the comprehensiveness of data is pivotal. For instance, facial recognition AI can exhibit biases due to restricted training data, leading to higher accuracy for some demographics over others.

In the realm of AI-enhanced admissions, a heavy reliance on historical data can unintentionally perpetuate past biases. This could result in an oversight of evolving admission criteria, such as changes to legacy admissions or shifts in affirmative action policies. A case in point is the University of Texas at Austin's decision in 2020 to abandon GRADE, a machine learning program used for Ph.D. applicant evaluations. Critics argued that the program, leaning on past admissions data, disadvantaged students from diverse backgrounds.

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ALGORITHMIC BIAS AND DATA OUTPUT INTERPRETATION

While AI models excel at finding correlations, they don't inherently discern causation, which can lead to misleading conclusions. This becomes evident in cases like Amazon's hiring algorithm, which inadvertently favoured male candidates, mirroring past employment trends. Simply identifying issues, such as students at risk, isn't sufficient for equitable decision-making; educators require actionable insights that align with institutional objectives.

A potent example of these biases in action can be seen in the findings of an investigation conducted by the technology news site, The Markup. They scrutinized 'Navigate,' a widely-used advising software developed by consulting firm EAB. Alarmingly, their research found that the software labeled Black students as “high risk” of not graduating from their selected major at a rate quadruple that of their white peers. This stark disparity in algorithmic predictions was aptly summarized by Ruha Benjamin, a Professor at Princeton University. he voiced concerns over how such skewed recommendations might mislead college advisors, resulting in Black, Latinx, Indegenous students being unduly discouraged from pursuing certain majors, all under the misleading veneer of advanced algorithmic suggestions.

Roxana Marachi, an education professor at San Jose State University, highlighted a past feature in the LMS Canvas that flagged students turning in late work, suggesting they might perform poorly. Such systems could erroneously flag students, particularly if assignments were submitted differently than expected. She advocates for transparency and student awareness of how their data is used, which is often not the case in educational settings.

Therefore, a thorough grasp of AI functionalities, strengths, and limitations is essential. When AI-generated insights diverge from human judgment, clear protocols should guide decisions, aiming for a seamless integration of tech-driven insights and human intuition to ensure fairness and precision.

3 THE INTERPLAY OF DATA AND HUMAN INTERACTION

While data-driven assessments provide a wealth of information, they can sometimes overlook nuances that are evident in human interactions. Machines, by their nature, interpret data literally, whereas human teachers can understand and adapt to contextual variables, like how a student's health might influence their academic performance. Despite the advancements in AI-driven assessment tools, the unique value of dedicated human educators remains paramount. A fully AI-operated classroom is still a distant and perhaps unfeasible concept. However, modern educators can utilize AI tools to handle routine tasks, freeing them up to invest more time in cultivating deeper relationships with their students. This enables them to offer a personalized educational experience, even in larger settings.

LEGAL CONCERNS 4

The legal concerns are primarily related to student privacy. Federal regulations emphasize student consent for data disclosure and their right to access and challenge their information. As AI's impact on decision-making grows, educational institutions may face increasing pressure to be transparent about how AI influences student outcomes. In response, some EdTech vendors such as Canvas' parent company, Instructure, emphasizes its commitment to data privacy. They've recently hired a privacy attorney and formed a privacy council consisting of educators and students to advise on data practices.

Furthermore, the rise of AI in education has illuminated gaps in regulations regarding accessibility, especially for students with unique needs. The Americans with Disabilities Act (ADA), enacted 32 years ago, promised transformative educational opportunities for students with disabilities and the neurodivergent. However, the rise of technology in education, while offering some benefits, has also introduced challenges. Schools are increasingly using techno-solutionist tools that often misinterpret and penalize neurodivergent behaviors. Remote proctoring programs, introduced during the COVID pandemic, can mislabel behaviors of students with disabilities as "suspicious," leading to unjust treatment. Additionally, biometric policing technology, which evaluates students against a "normal" behavior trend line, is finding its way into classrooms. Despite the ADA's intentions, technological advancements risk further alienating neurodivergent students, emphasizing the need for updated regulations that consider the implications of modern technology.

5 THE SHIFT IN EDUCATIONAL DECISION-MAKING

Private companies frequently gather and visualize educational data, leading to potential shifts in decision-making power. Such companies might not always prioritize the interests of essential educational stakeholders, especially students. Moreover, AI in education creates an "invisible infrastructure" by implicitly determining educational priorities. As a result, learning software might set hidden standards, potentially misaligned with traditional academic criteria. Furthermore, the inherent clarity AI systems require can sometimes lead to an overemphasis on narrowly defined objectives, sidelining broader educational goals such as fostering creativity. Tensions can also emerge due to divergent interests between tech developers, educational institutions, and students. A case in point is Mount St. Mary's University, where institutions prioritized their reputation, potentially compromising both the quality of education and the well-being of their students.

Some comments from Instructure's then-CEO, Dan Goldsmith, suggested monetizing predictive algorithms, raising concerns about prioritizing profit over student welfare. Ben Williamson, Sian Bayne, and Suellen Shay, scholars from the Universities of Edinburgh and Cape Town, expressed broader concerns about the use of big data in teaching. They argue that data-driven metrics might lead to a superficial evaluation of student success, potentially sidelining higher-order thinking in favor of easily measurable outputs. They link datafication to the commercialization of higher education, suggesting that the shift to digital platforms might alter how educators perceive students

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