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Teaching Smarter: Artificial Intelligence as a Tool for Student Success, Early Intervention and Assessment Design in Higher Education

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Abstract:

Student success in higher education has never been only about academic ability. It is about identifying students who are on the verge of failure or giving up and trying to get them back on the path of success before it is too late. It is about figuring out the right assessments to genuinely measure learning and giving the right feedback at the right time for students. Artificial intelligence has become an important tool to identify these structural issues and assist teachers rather than replacing them.

The goal of this paper is to understand three applications of AI that are most relevant to teachers who work to improve student success- predictive analytics and risk of early dropout identification, ongoing AI-assisted feedback and AI-supported assessment design that focusses on both quality and genuinity. All these points are examined from a teacher's perspective of roles that are practical, subject to change and what cannot be replaced by Artificial intelligence in student success.

One of the important conclusions of this study shows that the most important contribution of AI to student success is the reduction in response time of a teacher when a student experiences difficulty. Students earlier had to wait for their submitted assignments to be scored to understand their progress levels or planned meetings with teachers to find out how they were doing. AI, on the other hand creates ecosystems for continuous, ongoing support with the teacher at the centre of every support initiative needed. But the differentiating factor is the power of the information they have and at the speed at which they have it. On top of this, they can use the freed up time from routine tasks to spend with students who most need their attention.

Keywords: Artificial Intelligence, Student Success, Predictive Analytics, Automated Feedback, Assessment Design, Dropout Risk.

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Introduction:

Student dropout is one of the most expensive and ongoing issues in higher education. The numbers vary across institutions and disciplines but follow a similar pattern where high number of students enroll for courses but do not complete their qualifications. The irony is that the decision to quit is almost

never made suddenly but is an accumulation of disconnect over weeks or months between difficulties faced by students and missed opportunities for intervention by busy teachers who are responsible for hundreds of students simultaneously (Tinto,1993), (Bean, 1980).

It has been seen that feedback which is one of the single most powerful influences on student learning also faces a similar structural problem. The most useful feedback to a student is specific, timely and actionable and the kind of feedback that teachers can realistically provide at scale is frequently too general or sometimes delayed by weeks, and delivered often after the point where it can be acted upon (Hattie and Timperley, 2007), (Nicol and Macfarlane-Dick, 2006).

There are challenges in the design of assessments as well where teachers are expected to create tasks that measure real understanding, battle AI-assisted completions, identify students with different learning profiles and manage to grade assignments all while managing the existing traditional academic workloads adding to the stress levels of educators (Bearman et al, 2023), (Black and Wiliam, 1998).

Artificial intelligence does not magically make these issues go away but in turn it offers a set of tools that can help educators carefully solve these ongoing problematic structural conditions. This paper aims to understand how this practical transformation works reality across dropout prediction, feedback and assessment and more importantly the changing professional role of educators in an AI-assisted learning ecosystem (Zawacki-Richter et al, 2019), (Luckin et al., 2016).

AI and the Early Identification of Dropout Risk:

The behavioral indicators of risk of dropout are normally seen in student data much before it is observed by teachers. Research shows that measurable predictors of risk of dropout are seen within weeks or months of withdrawal with decreased engagement with digital learning platforms, irregular patterns in submission of assessments, reduction in discussions or participation in courses, and underperformance in initial assessments (Macfadyen and Dawson, 2010), (Siemens, 2013).

Learning analytics systems are equipped to collect and analyze these signals automatically. “Purdue University's Course Signals system” is one of the earliest and most studied systems that translates engagement data from learning management systems into risk ratings which are shared with students and their teachers in real time. The retention rates were seen to be much higher in students who received outreach prompts by “Course Signals” than comparable peers who did not receive them. The intervention effect was much more effective for students in the high risk category (Arnold and Pistilli, 2012).

A real time example of implementation of learning analytics is the “Open University UK” where engagement data of tens of thousands of distance learners, were analyzed and risk indicators were generated that allowed personal tutors to proactively contact students who showed early warning signs. Educators reported that the nature of their support responses changed from crisis reaction to proactive contact that could correct the course of a student’s outcome (Herodotou et al., 2020).

These systems need analytical judgment and not technical knowledge from teachers. A learning analytics platform generates a list of priority students whose engagement patterns show need for attention and not necessarily the remedy. In turn, an educator must treat a risk alert as a conversation starting point and deeply understand a student's circumstances and subject difficulty which an algorithm normally cannot do. The algorithm can identify which student needs be prioritized and then the teacher is the one who should determine what support that student needs (Holmes et al., 2022; Ferguson, 2012).

The limitations of predictive systems must be understood by teachers as models are trained on historical data that includes the student population that could have been influenced by historical patterns of disadvantage. A system that flags students from lower socioeconomic backgrounds as high risk could be because of students of that background having historically higher dropout rates. This may be a structural problem and not necessarily an individual student issue (Baker and Hawn, 2022). Teachers who understand this limitation are better suited to use this analytics data as a starting point for professional assessment and not as a substitute for it.

AI-Assisted Feedback: The Human Dimension and Efficiency:

The formative assessment as per Sadler's (1989) has been driven for three decades by a principle which states that students improve when they understand where they are currently and there they need to be and what they can do to bridge this gap. The problem of applying this principle at scale is that there is a structural problem of teachers not being able to generate specific, timely feedback for every student on every piece of work while working with large cohorts which essentially can be solved best with AI-assisted feedback (Sadler, 1989), (Shute, 2008).

Automated writing feedback tools such as Turnitin's and PaperPal have formative features which share paragraph wise feedback on structure of arguments, evidential support and citation conventions with real time submission. In cases such as a student who needs to submit an essay can get timely feedback at stage of drafting the essay this enabling a lucrative revision before even receiving the teacher's corrected copy. Research on automated writing assessments show positive effects on quality of revisions and final submission especially after multiple feedback inputs received by students before a assessment deadline (Yan et al., 2021; Deane, 2013).

The true potential of AI's feedback capacity can be seen with Intelligent tutoring systems. A meta-analysis conducted of 62 studies showed that well-implemented intelligent tutoring generates learning gains of roughly 0.76 standard deviations in relation to traditional classroom instructions closely resembling one-on-one human tutoring effects as per VanLehn's (2011). In both cases, feedback is delivered real time when a student makes an error and has a chance to understand it before misunderstanding a concept. There is a very tight window for effective correction and AI tools can operate within it consistently in a way that teachers can rarely do so (VanLehn, 2011), (Chi et al., 2020).

However, feedback generated by AI cannot comprehend the reasoning behind an argument made by a student. It can identify that a conclusion does not follow logically from the

previous paragraph, but it cannot derive whether the issue is due to poor reasoning or expression. It cannot judge academically and differentiate between a new perspective and a confused one. As per Winstone et al. (2019) , students report that they find feedback most useful when it comes from someone who is involved with their specific academic work and typically that is their teacher who can bring in that quality of engagement when AI has already taken care of the structural aspects of an assignment and allows the teacher to spend qualitative time with the student (Winstone et al, 2019), (Boud and Molloy, 2013).

AI in Assessment Design and Academic Integrity:

Several traditional unsuccessful assessment practices have received a wake up with the availability of generative AI tools capable of producing competent academic writing in response to standard essay prompts. Generative AI have highlighted drawbacks of essay questions that reward recall and assembly of existing knowledge which were submitted offline without verifying the authorship or measurement of learning goals (Cotton et al, 2023), (Kasneci et al, 2023).

The apt response to the work of generative AI is not detection but a recourse by teachers who understand the importance of knowledge application over mere summarisation thus in effect reducing the use of AI for dishonest purposes. AI tools can support this redesign at the task generation level by producing different assessment prompts at different difficulty levels, academic case study scenarios or oral examination question sets which can decrease the cost of workload of creating differential assessments (Bearman et al, 2023), (Nieto-Escamez and Roldan-Tapia, 2023).

Another underestimated practical application of AI is using generative AI to create assessment rubrics that are then finetuned by professional judgment of teachers and co-created by students thus having transparent open criteria which is applied consistently across cohorts before starting an assessment task. Research reflects that this helps students submit work that is more closely aligned with learning outcomes than those who understand requirements only post submission feedback (Gonzalez-Calatayud et al, 2021), (Sadler, 1989).

Academic integrity in the generative AI era needs more than a blanket prohibition or restricted usage permission. Teachers need clear guidance from institutions on what is appropriate AI use for their discipline specific assessment formats rather than institution-wide policies that does not differentiate between subjects. The highest integrity structures look at AI as a tool which needs credit and not as a threat to be detected and eliminated. Teachers transparently use AI in their own teaching practice are better equipped to guide students qualitatively than those who treat AI engagement as something to be questioned (Lodge et al, 2023), (Cotton et al., 2023).

The Teacher's Role in an AI-Supported Learning Environment:

Each of the three applications discussed above has reinvented the teacher's professional contribution rather than eliminate it. Risk identification systems have transformed teachers from crisis managers to proactive supporters. AI feedback tools activate the teacher attention from surficial correction to

academic engagement and AI assessments reduce teacher effort in generating tasks and helps them focus on design and educational judgment. But this does not reduce the professional efforts of teachers as routine work gets replaced by qualitative academic engagements and judgements (Popenici and Kerr, 2017), (Luckin et al, 2016).

This shift needs professional development that teachers in the current professional setups do not possess. Teachers who look at predictive analytics as only dashboards without understanding the assumptions, limitations, and suitable uses of the model are likely to make poor professional decisions than those without the dashboard at all. Teachers who introduce AI feedback tools without helping students understand what the automated feedback means will result in students engaging with feedback superficially and accepting AI approval as a quality signal which it is not designed to give (Tammets and Ley, 2023), (Huang et al, 2023).

The relational dimensions of teaching are where teachers play a meaningful role and do not include AI. Learning analytics systems can inform teachers about situations where students engagement with course materials had reduced. But it cannot fathom the reason behind the reduction which could be because of overwork, a family crisis, a loss of interest that only a teacher can identify and bring back to life keeping in mind the needs of the student. The human intervention of a teacher including professional knowledge, emotional intelligence and academic expertise cannot be replaced by an AI system. Educators can thus involve themselves in qualitative engagement with students by outsourcing work that AI can handle efficiently (Holmes et al, 2022), (Popenici and Kerr, 2017).

What Gets in the Way:

The applications of AI mentioned in this study are not theoretical in nature. According to research, predictive analytics, AI-assisted feedback and AI-supported assessment design have been implemented in several institutions across multiple countries and their impact on student outcomes have been documented. Therefore, the reason for restricted adoption is not because of lack of previous exploration but a gap in availability of tools and the professional development needed for its usage for educators (Zawacki-Richter et al, 2019), (Tammets and Ley, 2023).

Institutional AI training for teachers remains behind the speed of tool deployment. The 2021 UNESCO global survey of AI in education found that several institutions had adopted AI tools without sufficient teacher training and development leading to technical adoption without academic integration (UNESCO, 2021). Teachers who use these tools without training end up replicating existing practices in a more efficient manner instead of trying to redesign those practices to improve student outcomes.

Data literacy is necessary for effective use of learning analytics which most of the teacher development programs do not include. These training programs must not be treated lightly and must include how to interpret risk dashboards and metric representations, calibrating suitable professional responses. Institutions that invest in this professional development see substantially better outcomes than those who stop at mere dashboard readings

(Macfadyen and Dawson, 2010), (Siemens, 2013).

Ethical dimensions of AI-assisted teaching need institutional frameworks not individual reforms. These include answering questions about learning analytics platform in relation to ownership of student risk data, duration of retention, how student engagement is being monitored and how predictive labels affect teacher expectations of individual students. Governance and policy level institutional decisions place an unfair burden on individual teachers and put unconsenting students at risk (Holmes et al, 2022), (Baker and Hawn, 2022).

Conclusion:

There is no one answer to the question of whether AI will improve student success as it depends entirely on how it is used by educators. When AI tools are used without training or institutional support, they produce dashboards which are not used effectively by anyone or generate feedback which is not used by students and create assessment tasks that produce the same integrity problems as the tasks they tried replacing with AI. Educators are able to rely on AI tools, when it is used with a professional purpose within a structured governance framework which protects student rights and teacher freedom. They are able to utilize the information to respond to student difficulties and pivot from failure and dropouts and share feedback that bridge the gaps between academic intentions and time saved from routine tasks to handle qualitative issues that matter most (Luckin et al, 2016), (Zawacki-Richter et al, 2019).

The value of a teacher's role in a well-designed AI-assisted learning ecosystem is only enhanced and not diminished. AI can handle monitoring, share first level feedback and complete tasks but the higher order roles of understanding students well enough to know why they are struggling or to push their thinking beyond a prompt or a rubric cannot be handled by an algorithm. A purposeful AI integration ultimately offers time and space for an educator to handle more qualitative tasks (Popenici and Kerr, 2017), (Holmes et al, 2022).

Institutions need to match their appreciation of AI tools with equal investment in teacher development, governance frameworks and academic redesigning. Bridging the gap between institutional needs, teacher development and potentional use of these AI tools is the most urgent task in AI-assisted education today (UNESCO, 2021), (Tammets and Ley, 2023).

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