Chapter 5

Augmented or Automated: Examining the Role of AI in Reimagining Instructional Design in Higher Education

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Introduction

Rapid advancements in AI (artificial intelligence) and big data analytics have ushered in transformative possibilities for HE (higher education) and opened up new possibilities for enhancing teaching and learning. This chapter critically examines the applications of AI in instructional design, assessing current use cases and potential future implementations. It discusses the impact of AI on learning analytics, student modelling, intelligent and adaptive learning systems, AI teaching assistants, and tutors. The analysis aims to identify the trade-offs between augmentation and automation in learning design processes, emphasising the need for ethical and equitable applications. The chapter also explores policy implications to ensure widespread access to beneficial AI technologies. While AI presents opportunities to enhance teaching and learning, the chapter underscores the importance of preserving human expertise and agency in education. However, the rapid development of AI technologies also raises significant challenges, including ethical concerns, integration costs, and the potential displacement of educators' roles. These complexities demand a thoughtful approach that balances innovation with caution. Examples from industries like healthcare and finance demonstrate the potential of AI to revolutionise practices while maintaining human oversight.

Overall, the analysis presented in this chapter aims to shape the discourse on optimising the incorporation of AI capabilities in HE learning design without diminishing the vital role of human expertise and agency. AI and machine learning have emerged as potentially transformative forces in HE. As assumptions about the nature of work, types of careers, and requisite skills evolve rapidly, experts argue that AI will play a pivotal role in building the capabilities of future generations (cf. Joshi, Rambola, & Churi 2021). Harnessing these exponential technologies also represents an unprecedented opportunity to improve how we teach and structure learning. From serving as virtual teaching assistants to providing adaptive curricular pathways, AI-driven tools have already begun reshaping instructional models.

However, to date, the integration of AI in education has been largely *ad hoc* and narrow in scope (Hutson, Jeevanjee, Vander Graaf, Lively, Weber, Weir, Arnone, Carnes, Vosevich, Plate, Leary, & Edele 2022). A more strategic examination is required to determine appropriate and ethical applications that enhance student outcomes without compromising vital human judgement and agency. This chapter analyses the current state and future trajectory of AI in transforming instructional design, exploring trade-offs inherent in augmenting versus automating learning design processes.

AI Driven Learning Analytics and Student Modelling

The advent of big data in HE *via* enterprise systems, online programmes, and learning management platforms means that vast quantities of student data exist that hold potential to inform learning design improvements (Darvishi, Khosravi, Sadiq, & Gašević 2022; Ouyang, Wu, Zheng, Zhang, & Jiao 2023). AI techniques offer new methods to extract actionable insights, predict future behaviours, and personalise learning pathways from this sea of information (Krenn, Buffoni, Coutinho, Eppel, Foster, Gritsevskiy, Lee, Lu, Moutinho, Sanjabi, Sonthalia, Tran, Valente, Xie, Yu, & Kopp 2023).

Several IHEs (institutions of higher education) such as the Open University UK (Boroowa & Herodotou 2022) have already implemented PLA (predictive learning analytics) dashboards that harness natural language processing and neural networks. These PLA systems (cf. Ramaswami, Susnjak, Mathrani, & Umer 2023) analyse real-time streams of student academic and engagement data to flag at-risk students who may require early intervention or support services (Nurhadi, Hussin, & Demon 2021). Automated notifications and alerts enable advisors to connect students with resources like tutoring (Ahmad, Iqbal, El-Hassan, Qadir, Benhaddou, Ayyash, & Al-Fuqaha 2023; Caspari-Sadeghi 2023), counselling (Majjate, Bellarhmouch, Jeghal, Yahyaouy, Tairi, & Zidani 2023), or peer-mentoring (Dede & Lidwell 2023) specifically when they need help. Using PLA for targeted outreach has been found to positively impact student retention and success (Namoun & Alshanqiti 2020; Ifenthaler & Yau 2020). For instance, the Open University UK reported a 15% increase in retention rates after implementing predictive analytics dashboards. However, the effectiveness of PLA depends heavily on the quality and bias of input data. Institutions must adopt measures such as regular audits and diverse data sampling to ensure fair and accurate outcomes.

Recent important developments in the area of AI include improved language technologies like sentiment analysis which are also being incorporated in next generation learning analytics platforms to assess student motivation, confidence, and psychological states by scanning discussion posts, assignment reflections, and advisor meeting notes (Yadav & Vishwakarwa 2020; Kastrati, Dalipi, Imran, Pireva Nuci, & Wani 2021; Shaik, Tao, Dann, Xie, Li, & Galligan 2023). By uncovering affective signals in students' unstructured writings, advisors can identify emerging issues to provide timely assistance. Contextualised insight into the 'whole student' experience allows learning design refinements addressing not just academic but also meta-cognitive and social-emotional development.

Today, developing AI environments that support exploratory learning, particularly in MOOCs (Massive Open Online Course), which require sophisticated student models to provide adaptive support seem to be in vogue (Conati & Lallé 2023). Nevertheless, building adaptive support for open-ended exploratory learning remains a major challenge (Conati & Lallé 2023).

Intelligent and Adaptive Learning Systems

Intelligent tutoring, adaptive learning, and recommender systems are a few notable instances of AI-enabled learning environments. According to Hasanov, Laine, and Chung (2019), an intelligent tutoring system employs AI approaches to emulate a human tutor, hence enhancing learning outcomes through improved student assistance. Recommender systems are defined as 'software tools that provide suggestions for potentially useful items to someone's interest based on machine learning and information retrieval techniques' (Aamir & Bhusry 2015, cited by Syed, Palade, Iqbal, & Nair 2017:1). According to Pliakos, Joo, Park, Cornillie, Vens, and Van den Noortgate (2019), as well as Xie, Chu, Hwang, and Wang (2019), ALSs (adaptive learning systems) are customised learning environments that adjust to students' learning styles, the order and complexity of the tasks, the feedback period, and their preferences. Through automated feedback cycles built into the systems, these platforms encourage students to keep track of their educational progress.

AI advancements are also enabling more responsive and tailored learning content. On the one hand, intelligent tutoring systems incorporate extensive subject matter expertise to provide personalised guidance scaffolding students from simple to complex concepts (Paladines & Ramirez 2020; Mousavinasab, Zarifsanaiey, Niakan Kalhori, Rakhshan, Keikha, & Ghazi Saeedi 2021). These AI systems assess individual student needs, dynamically adjust activities to address knowledge gaps and supply real-time hints during problem solving. Research indicates that such adaptive learning technologies enhance concept retention and reduce attrition for diversified students, including low-performing students (Akyuz 2020).

On the other hand, AI techniques like natural language generation and information retrieval as well as ALSs (Kabudi, Pappas, & Olsen 2021) facilitate the automated curation of customised course learning materials from existing repositories (Tlili, Zhang, Papamitsiou, Manske, Huang, Kinshuk, & Hoppe 2021). Text and data mining methods help assemble relevant exercises, readings, videos, and cases into unique sequences meeting defined learning outcomes. Automating the indexing, recommendation, and assembly of personalised content modules based on parameters like learning preference, prior learning and/or mastery and target competencies, stands to make course creation more scalable while providing a tailored learning path (Osadcha, Osadchyi, Semerikov, Chemerys, & Chorna 2020).

However, despite promising applications, many intelligent and ALSs remain narrow in scope, supplemental rather than core to learning experiences. One notable challenge is the scalability of these systems, particularly for resource-constrained institutions. The infrastructure required for ALSs, including advanced computing systems and continuous updates, often limits their adoption. Moreover, the unequal distribution of resources can create disparities in access to these personalised learning tools, further widening the digital divide. Truly personalised, responsive platforms enabling student agency and control and positively impacting on learning outcomes remain rare (Bernacki, Greene, & Lobczowski 2021). Similarly, a meta-analysis by Major, Francis, & Tsapali (2021) indicated that technology-supported personalised learning resulted in significantly positive learning outcomes for school-aged children in low- and middle-income countries. Correlations have also been identified between the use of personalised and responsive e-learning platforms and students' performances (Mustafa 2021). A study by Leem (2023) highlights the significant positive effect that personalised and responsive online learning platforms have on learning outcomes, which underscore the importance of considering the interaction between content, teaching, and platform design to enhance student engagement and achievement. AI tools, such as cognitive tutors and adaptive learning systems, provide personalised learning paths, improving student engagement and academic performance (Bilad *et al.* 2023; Legowo *et al.* 2024).

Further research has delved into specific factors such as student-to-student dialogue, course structure, and technology quality, which are found to positively impact student satisfaction, which in turn is correlated with e-learning outcomes. These improvements suggest solutions like enhancing the teaching platform and course design, as well as a careful selection of software and teaching aids (My, Tien, My, & Le Quoc 2022). Moreover, individual student support systems and adaptive pedagogical approaches within personalised and responsive platforms are posited to potentially impact learning outcomes in online education (Singh & Alshammari 2023). Another perspective offered by Seo, Tang, Roll, Fels, and Yoon (2021) focuses on the impact of AI systems on student-educator interaction in online learning, discussing concerns such as agency and surveillance. The paper recommends that AI systems should prioritise explainability and human-in-the-loop design to positively support these interactions.

Implementing platforms such as arabi.id – a personalised and responsive LMS (learning management system) – proved to have a statistically significant positive impact on the language skills of non-native Arabic students (Ismail, Mun'im Ahmad Zabidi, Paraman, Mohd-Yusof, & Rahman 2023). Similarly, engaging with educational resources like podcasts in a personalised manner has been found to positively influence students' learning outcomes (Facer, Abdous, & Camarena 2009).

The benefits of these platforms do not preclude challenges, however. Adaptations can include embedding feedback systems developed through a participatory design with both students and educators to mitigate the risks associated with the adoption of such personalised tools. The complexity of replicating dynamic educator-student interactions makes automating comprehensive course experiences elusive. Ethical issues around data privacy, uneven access and overreliance also give pause. Yet the trajectory toward augmented, if not fully automated course assembly is clear.Top of FormBottom of Form

AI Teaching Assistants and Tutors

As AI capabilities advance, one emerging application is AI teaching assistants that support routine instructional tasks and augment human teaching staff. Chatbot technologies allow customised student queries about assignments, deadlines, and course logistics to be addressed 24/7 without overburdening faculty (Tian, Risha, Ahmed, Lekshmi Narayanan, & Biehl 2021). A systematic review of chatbot applications in education found that chatbots can provide instant responses to students, improve student engagement, and enhance learning outcomes. Tegos, Demetriadis, and Tsiatsos (2014) found that conversational agents can trigger productive dialogue among students, leading to improved learning outcomes. Additionally, AI chatbots have been used to provide personalised support for students, including pre-enrolment requirements, university-class schedules, and assessment timetables. These technologies have also been employed to facilitate practice and thus enhance specific communication skills, such as motivational interviewing skills and workplace communication for health workers (Kuhail, Alturki, Alramlawi, & Alhejori 2023). Here real-time personalised feedback sharpens performance. Automating the answering of repetitive questions enables teaching staff to focus on higher value instructional duties. Over and above this, studies indicate that AI teaching assistants can match human teaching assistants in terms of response speed and helpfulness, particularly in programming education (Lee, Myung, Han, Jin, & Oh 2023). AI teaching assistants have been effective in guiding novice learners through complex tasks by breaking them down into manageable subgoals, demonstrating their potential in structured learning environments (Lee *et al.* 2023).

AI teaching assistants leverage data mining, speech recognition, and natural language processing to assess open-ended verbal student responses, either correcting errors or indicating gaps for educators to discuss (Paladines & Ramirez 2020). However, the absence of EI (emotional intelligence) in AI remains a critical limitation, as these systems cannot interpret non-verbal cues or provide empathetic support. Institutions should implement blended models where AI handles routine tasks, enabling educators to focus on mentorship and complex teaching interactions. This approach ensures that students benefit from efficiency gains without losing the human connection vital for holistic education. For high-enrolment foundation courses, automating basic content comprehension checks and written feedback remarking saves faculty grading time to concentrate on advancing conceptual mastery (Çekiç & Bakla 2021). Sophisticated neural networks have achieved sufficient semantic understanding abilities to provide scoring agreements with instructors above 90% across various subjects (Ariely, Nazaretsky, & Alexandron 2023).

ITSs (Intelligent tutoring systems) have been shown to improve learning outcomes by providing tailored feedback and support, thus enhancing the overall educational experience (Bilad, Yaqin, & Zubaidah 2023). However, while AI tutoring assistants effectively supplement teaching, fully replicating deeper instructor roles remain improbable in the foreseeable future. The need for emotionally supportive, dynamically sensitive human engagement constitutes one constraint, especially for younger students (Akyuz 2020). Most significantly, the ingenuity gap of creatively inspiring students or customising personal growth pathways eludes the existing AI. At best teaching assistants provide task augmentation, however, there are also some noteworthy risks. First, an increased use of AI systems may lead to reduced student interaction with real humans, potentially impacting social connections and EI. Second, even though this is improving, AI's lack of EI and the inability to read and perceive unspoken signals such as tone and body language may hinder effective communication and teaching (Luong, Sivarajah, & Weerakkody 2021), emphasising the need for human input in conjunction with AI, rather than as a sole replacement for educators. Third, an overreliance on AI can potentially reduce students' capacity for independent thought and critical thinking, as they may become increasingly reliant on the software, impacting their learning outcomes (Kamalov, Santandreu Calonge, & Gurrib 2023). Then there is the fact that AI algorithms may struggle to provide the same level of innovative and creative approaches that human educators can offer, potentially impacting the overall engagement and effectiveness of educational materials (Qadir 2023). AI models may struggle with individualised learning needs and perpetuate biases if trained on biased data, leading to potential gaps or inaccuracies in the educational content (Schwartz, Vassilev, Greene, Perine, Burt, & Hall 2022; Hagendorff, Bossert, Tse, & Singer 2023).

Challenges and Considerations for Implementation

Despite burgeoning investment, adopting AI-based instructional enhancements face barriers concerning system biases, equitable access, changing staff roles, and ethical data usage that warrant consideration. One concern around increasingly data-dependent academic decision-making involves issues of fairness, transparency, and accountability (Nassar & Kamal 2021). Analytics predictions informed by datasets with hidden biases may scale systemic disadvantages rather than foster inclusivity (Archer & Prinsloo 2020). Interpretability around AI recommendations requires improvement to avoid an overreliance on algorithms lacking explanatory audit trails.

Unequal access and affordability issues also persist regarding new technologies, potentially exacerbating achievement gaps (Deganis, Haghian, Tagashira, & Alberti 2021). Students lacking home broadband (Hampton, Fernandez, Robertson, & Bauer 2020) or sufficient digital literacy skills (Reisdorf & Rhinesmith 2020) could remain excluded despite an institutional adoption of AI innovations. Disparities between well-resourced early adopters actively prototyping applications and smaller colleges also seem likely absent deliberate effort. These dynamics emphasise the necessity of equity-centred design and deployment policies promoting responsible innovation (Hendricks-Sturrup, Simmons, Anders, Aneni, Clayton, Coco, Collins, Heitman, Hussain, Joshi, Lemieux, Novak, Rubin, Shanker, Washington, Waters, Harris, Yin, Wagner, Yin, & Malin 2023).

Further tensions stem from AI's impact on educator job roles and a sense of professional purpose, should automation limit specialised expertise application while prioritising efficiency (Zawacki-Richter, Conrad, Bozkurt, Aydin, Bedenlier, Jung, Stöter, Veletsianos, Blaschke, Bond, & Broens 2020). To address these challenges, institutions could establish cross-disciplinary committees that include educators, technologists, and ethicists to oversee AI implementation. Additionally, policies must prioritise inclusivity by offering subsidies for underprivileged students and ensuring that AI platforms are accessible to users with disabilities. These measures can help bridge the gap between well-resourced and resource-constrained institutions, fostering equitable access to AI benefits. Faculty adoption pivots on maintaining educator agency over tools intended to augment and not prescribe practice. Insufficient communication around evolving AI capabilities and participatory decision-making risk alienating stakeholders within complex political university environments wary of disruptive technologies. Transforming organisational culture to balance innovative experimentation with core values of openness, academic freedom, and humanistic education stands critical (Bozkurt, Junhong, Lambert, Pazurek, Crompton, Koseoglu, Farrow, Bond, Nerantzi, Honeychurch, & Bali 2023).

Ethical Frameworks for AI in Higher Education: Augmentation vs. Automation

The distinction between AI as a tool for augmentation versus automation in HE lies at the heart of developing ethical frameworks. Augmentation refers to AI enhancing human capabilities, such as improving educators' efficiency or providing personalised support for students, while automation entails the replacement of certain human functions with AI systems. Ethical considerations for these two paradigms differ but are deeply interconnected, as both approaches aim to maximise the benefits of AI while minimising potential harms.

In the context of augmentation, ethical frameworks must focus on supporting human agency. When AI is used to assist educators, such as through intelligent tutoring systems or AI teaching assistants, its role should be to empower rather than replace. For instance, AI can provide personalised feedback to students on routine tasks, enabling educators to focus on higher-value activities like fostering critical thinking and mentoring. However, if augmentation is poorly implemented, there is a risk of over-reliance on AI, leading to a deskilling of educators and diminishing their professional judgement. Ethical frameworks must thus include provisions for capacity-building, ensuring educators to have the skills to effectively use and supervise AI tools. Transparency in how AI generates recommendations or performs tasks becomes crucial in these scenarios to maintain educators' confidence and control over the process.

When AI is applied for automation, such as in grading or administrative tasks, ethical concerns shift towards accountability and fairness. For example, automated grading systems might inadvertently disadvantage students whose work does not align with the algorithm's design, such as creative or unconventional approaches to problem-solving. Ethical frameworks must mandate regular evaluations of such systems to detect and mitigate biases and inaccuracies. Additionally, clear protocols for redress must exist, ensuring students to contest automated decisions. This is particularly important in high-stakes applications like admissions or predictive analytics for at-risk students, where automation could amplify systemic biases if not carefully monitored.

Inclusivity is a cornerstone for both augmentation and automation. Augmented systems should cater to diverse learning preferences, enabling equitable access to personalised education. Meanwhile, automated systems must be designed to accommodate students with disabilities or varying levels of digital literacy. For instance, an automated learning analytics platform that identifies students needing extra support should ensure that these insights are accessible and actionable for both students and educators, regardless of technological proficiency. Adaptive learning technologies represent a significant advancement in personalised education, leveraging sophisticated algorithms to tailor learning experiences to individual student needs. Systems like AutoTutor exemplify this approach, using adaptive algorithms to customise content based on learners' existing skills and knowledge. This ensures that students are challenged appropriately while receiving the support necessary to progress effectively (Lippert, Gatewood, Cai, & Graesser 2019; Shi, Wang, Zhang, Shubeck, Peng, Hu, & Graesser 2021). Moreover, AutoTutor incorporates six major learning affordances that facilitate the mastery of complex material, an essential feature for students with low literacy skills, enabling them to overcome significant educational barriers (Lippert *et al.* 2019; Shi *et al.* 2021).

The user-centred design of adaptive learning systems further enhances their efficacy, focusing on creating simple and intuitive interfaces that reduce cognitive load. These accessible designs cater for learners with diverse technological proficiencies, ensuring broader adoption and usability (Shi *et al.* 2021). Additionally, these systems often integrate conversational agents and interactive elements to boost engagement and motivation. For adult learners, who may face challenges in traditional educational settings, these features can significantly enhance self-efficacy and drive, making education more accessible and impactful (Hollander, Sabatini, & Graesser 2021; Shi *et al.* 2021).

Finally, the principle of human-in-the-loop emerges as a vital ethical safeguard bridging augmentation and automation. The principle of HITL (human-in-the-loop) in education underscores the collaborative interaction between humans and AI to enhance learning experiences. This approach emphasises the importance of human oversight, critical evaluation, and empathy, ensuring that AI systems align with human values and educational needs. HITL fosters a partnership between educators and AI systems to create adaptive learning environments, where AI analyses student data and identifies patterns while humans provide contextual understanding and emotional support. This synergy enables personalised learning experiences that address both cognitive and affective dimensions of education (Tong & Lee 2023).

The HITL model also addresses ethical concerns by ensuring that human judgement remains integral to decision-making processes in AI applications. By positioning humans as ‘fellow workers’ who interpret and validate AI outputs, the approach enhances the ethical legitimacy of AI in educational settings. This safeguards against the risks of biased or inappropriate decisions, as educators retain the authority to evaluate and contextualise AI recommendations (Salloch & Eriksen 2024).

Furthermore, HITL encourages interdisciplinary integration, drawing on insights from diverse fields such as psychology, computer science, and pedagogy to improve AI technologies in education. This cross-disciplinary collaboration is critical for developing AI systems that are not only technically robust but also empathetic and responsive to the nuanced needs of learners (Hutson & Plate 2023).

While the HITL principle offers significant advantages by balancing the strengths of human and machine intelligence, it also raises concerns about a potential over-reliance on AI, which could diminish human agency in learning processes. Striking the right balance between technological innovation and human input remains a critical challenge, requiring ongoing evaluation and adaptation of HITL frameworks to ensure they serve educational goals without undermining the central role of educators and learners. Whether AI augments or automates processes, human oversight should always remain integral to decision-making. This ensures that ethical judgement, empathy, and contextual understanding – currently, qualities uniquely human – are not overshadowed by efficiency gains. For example, while an AI system might recommend interventions for struggling students, educators must have the final say, informed by their personal interactions with students.

In short, ethical frameworks must be tailored to reflect the dual role of AI as both an augmentation and an automation tool in HE. By addressing issues of transparency, accountability, fairness, and inclusivity, these frameworks can guide institutions in leveraging AI responsibly while preserving the essential human elements that define education. This balance ensures that AI enhances the teaching and learning process without compromising the values and agency integral to HE.

Discussion, Recommendations, and Conclusion

The pace of advancement in AI will constantly accelerate, making proactive yet judicious integration into instructional systems imperative. From learning analytics to intelligent tutors and automated content creation, AI offers enhancements that could enrich HE. However, we must equally guard against over-exuberance where embedded biases, unequal access, deskilling or dehumanising effects arise from an uncritical adoption of AI.

The transformative potential of AI in HE is evident across various dimensions, from learning analytics to ITSs. The integration of AI into instructional design holds promise for enhancing personalised learning experiences and optimising educational outcomes. However, the current landscape reveals a somewhat fragmented implementation of AI technologies in education. While PLA and ALSs showcase significant advancements, there remains a need for a more cohesive and strategic approach to leverage the full potential of AI.

The emergence of AI-driven tools for student support, such as chatbots and predictive analytics dashboards, signals a shift toward more proactive interventions. These technologies enable a timely identification of at-risk students, facilitating early intervention strategies and support services. The ALS showcases a move towards personalised education, addressing individual student needs and dynamically adjusting content based on performance. Despite these advancements, the discussion also acknowledges the current limitations, emphasising the importance of striking a balance between augmentation and automation. The complexities of replicating dynamic educator-student interactions and the need for emotionally supportive, human engagement remain crucial considerations.

Moreover, challenges related to system biases, equitable access, and changing staff roles need careful attention. The potential benefits of AI should not exacerbate existing inequalities and strategies, for responsible innovation must be integrated into the implementation process. Ensuring transparency, fairness and accountability in AI-driven decision-making becomes paramount.

With all these in mind, there are some recommendations I would like to put forward. The first one relates to policy and strategy. Institutions should develop clear metrics to evaluate AI's impact, such as student engagement rates, retention improvements, and equity benchmarks. Additionally, AI policies must be dynamic, allowing for periodic review and adaptation to incorporate technological advancements and evolving educational needs. Long-term strategies should focus on building partnerships with AI developers to co-create tools tailored to HE's unique requirements. Institutions need to adopt a strategic and cohesive approach to integrating AI into instructional design, aligning technology implementation with educational objectives. As such, content developers and policymakers should prioritise equity-centred design principles to ensure that AI applications do not exacerbate existing disparities in access and outcomes. To make this a reality, educational institutions have to implement comprehensive faculty development programmes to enhance educators' understanding and utilisation of AI technologies, fostering a balance between human expertise and technological augmentation. Further, there is a need to foster a collaboration between educational experts, technologists, and ethicists to ensure a wholistic approach that addresses the social, ethical, and educational implications of AI in HE.

Finally, while AI presents an immense potential for transforming HE, a careful consideration of ethical, social, and pedagogical dimensions is essential. A strategic and collaborative approach, coupled with ongoing research and dialogue, will be instrumental in harnessing the benefits of AI to enhance learning outcomes without compromising the essential role of human agency in education. The journey towards an optimised integration of AI in HE requires a balance between innovation and preservation of core educational values. Moving forward, a guiding perspective should emphasise AI as enhancing educator capabilities rather than replacing teaching roles. Implementation policies must promote ethical data usage, systemic inclusivity, and faculty autonomy. Beyond functionalist lenses and narrowly defining measurable analytics improvements, we need wholistic assessments weighing social, emotional, and civic growth central to HE's formative mission, yet less quantifiable. Ultimately by foregrounding cooperation, wisdom, and responsibility as educational values no less important than efficiency or personalisation, IHEs can fruitfully pioneer AI systems harmonising automation with our deepest humanity.

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1 No initials are provided for this author.