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Leveraging Artificial Intelligence in Higher Education

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Abstract

This concept paper explores the adoption of artificial intelligence (AI) in higher education, arguing that such integration must be guided by established teaching and learning theories, rather than purely technological models like TPACK and TAM. While AI presents opportunities for enhanced teaching, learning and administrative efficiency, it also raises concerns about academic authority, digital competence, and ethical implications. Drawing on Vygotsky's social cognitive theory, particularly its emphasis on cultural tools and social mediation, we propose a methodological approach that analyses higher education components, their interrelationships, and the formation of an institutional data pool. This Vygotsky-inspired framework advocates for leveraging AI through an institutional content management system (CMS) to foster collaborative knowledge construction. The paper addresses key challenges, including utopian-dystopian divides, ideological biases, and the need for new AI discourse, thereby contributing to a theoretically grounded model for AI integration in higher education.

Keywords: Artificial intelligence (AI), Higher education (HE), content management system (CMS), Vygotsky

Introduction

What is this AI doing in my higher education?

Higher education is experiencing rapid change driven by automation and artificial intelligence (AI), prompting fundamental questions about human roles in teaching and learning (Hemachandran et al., 2022; O'Dea & O'Dea, 2023). While AI is often promoted as enhancing human cognition, its integration also diffuses authority among lecturers, administrators, corporations, machines, and students (Bearman et al., 2023). Global spending on AI in HE is forecast to reach $6 billion by 2025, led by China and the United States (Illic et al., 2021). AI features prominently in learning management systems (LMS) and standalone products marketed through conferences and open educational resources (Bearman et al., 2023; Bratu et al., 2019; Ghergulescu et al., 2019, 2021; Lynch & Ghergulescu, 2016, 2019; Montandon et al., 2018). Rising costs may increase tuition fees and reduce enrolments in neoliberal economies (Aldosari, 2020) 2020; Pityana, 2005), pushing institutions toward distance offerings, micro-credentials, and AI-enabled efficiencies.AI is frequently framed as an "inevitable change" (Bearman et al., 2023, p. 369), echoing earlier shifts such as massification (Deem, 1998) and commodification (Mollis & Marginson, 2002). This paper focuses on four core challenges: (1) algorithmic bias and fairness, (2) privacy and data protection, (3) academic dishonesty, and (4) resistance rooted in commodification and loss of agency (Stahl & Wright, 2018; Huang, 2023; Kamenskih, 2022). We address these through Vygotsky's social constructivism, treating AI as a cultural tool mediated within the ZPD (Vygotsky, 1978).

In cognitive psychology, intelligence comprises perception, language, learning, reasoning, problem-solving, and reflection. AI, originating in Turing's work (Crompton & Burke, 2023), now refers to "computing systems that are able to engage in human-like processes such as learning, adapting, synthesizing, self-correction and the use of data for complex processing tasks" (Popenici et al., 2017, p. 2). Deep learning and tools like ChatGPT surpass human processing speeds (Mollick, 2006) yet provoke concerns about human authority. We follow Bearman et al. (2023, p. 381) in calling for new language that moves beyond human/machine and utopia/dystopia dualisms. Leveraging AI in HE means strategic utilisation to augment human capabilities through ethical, pedagogically grounded integration, with Vygotsky's framework as the optimal guide (Vygotsky, 1978).

The relationship between AI and HE: We have art supplies, but we do not know if we want to draw, paint, or sculp

In the tradition of cognitive psychology, "intelligence" has numerous interrelated components—perception, language, learning, reasoning, problem solving, and reflection. The contested notion of "artificial intelligence" has a rich history that is beyond the scope of this paper. In short, the term has its roots in the work of Alan Turing in the 1930s (Crompton & Burke, 2023), the "father" of computers per se, and his seminal quest to both mimic and exceed the limits of human intelligence. A current definition of AI is "computing systems that are able to engage in human-like processes such as learning, adapting, synthesizing, self-correction and the use of data for complex processing tasks" (Popenici et al., 2017, p. 2). The central questions about what human intelligence is and how it functions remain relevant today. It is not surprising that the inclusion of AI in HE has been met with resistance from the academy because AI raises questions about both human intelligence and human authority (Bearman et al., 2023).

There have always been fears that computers will surpass human intelligence. Historically, such fears were illustrated by the Turing test, which was based on the notion that humans would be able to distinguish between computer and human responses to questions. "(H)uman psychology" is seemingly distinct from "machine psychology" (Hemachandran et al., 2022, p. 2), however, connectionist functional models of the brain are used. Neurons are digital processors, and the brain is a computing machine. Moore's law, which states that the speed of computers, as measured by the number of transistors contained on a single chip, will double every year or two, continues to hold (Mollick, 2006). This means that the speed of data processing by machines is at levels far beyond human capability. In "deep learning" models, where machine learning involves multiple layers beyond simple input and output, machines can "learn" unsupervised, identifying features without prompting. The more recent and wildly successful marketing campaign of the CHATGPT natural language processing model has amplified these discussions.

Leveraging artificial intelligence (AI) in higher education (HE) is defined as the strategic utilisation of AI technologies to maximise advantages, focusing on integration that augments rather than supplants human capabilities. This approach emphasises AI's role in enhancing teaching, learning, and administrative processes through ethical, collaborative, and pedagogically grounded methods. The optimal way to achieve this is via a Vygotsky-inspired framework, where AI functions as a "cultural tool" that mediates social learning processes by facilitating scaffolding, the zone of proximal development (ZPD), and collaborative knowledge construction within institutional ecosystems, such as content management systems (CMS). By treating AI as an extension of social mediation, HE institutions can address challenges like ideological biases and authority diffusion while promoting equitable, human-centred innovation.

The benefits of AI in HE

The benefits of AI in higher education are substantial, particularly when framed through a Vygotsky-inspired lens. Here, AI serves as a cultural tool, or an external mediator of thought and learning (Vygotsky, 1978), that supports social constructivism by enabling dynamic, interactive knowledge construction (Tapalova & Zhiyenbayeva, 2022; Villatoro Moral & de-Benito Crosseti, 2022). Rather than replacing human elements, AI augments them, acting as a scalable "more knowledgeable other" that provides adaptive scaffolding to guide learners through their zone of proximal development (ZPD), or the gap between what a student can achieve independently and what they can accomplish with appropriate guidance.

The key benefit of AI in higher education is that it can deliver personalised learning at scale (Crompton & Burke, 2023; Mutiga et al., 2025; Welch Bacon & Gaither, 2020; Li et al., 2021). AI analyses individual learning patterns, strengths, weaknesses, pace, and preferences in real time to tailor content, resources, and pathways (Harati et al., 2021; Hooda et al., 2022). This creates student-centred experiences that accommodate diverse styles and address learning gaps efficiently, leading to improved outcomes such as higher post-test scores, increased self-directed learning time, and greater literature engagement in fields like medical education (Crompton & Burke, 2023; Li et al., 2021Welch Bacon & Gaither, 2020).

By continuously calibrating difficulty and support, AI optimises the ZPD, keeping learners in an optimal challenge zone that promotes growth without frustration or overload, aligning with dynamic path optimisation rooted in reinforcement learning principles (Mutiga et al., 2025). Examples include that adaptive platforms provide customised lesson plans, immediate adjustments (e.g., ramping up difficulty for quick mastery or offering prerequisites for struggles), and personalised self-assessment) (Meng et al., 2025; Crompton & Burke, 2023; Xu & Ouyang, 2022; Menggo et al., 2022).

Secondly, AI can provide adaptive scaffolding and support. AI delivers context-sensitive hints, prompts, feedback, and guidance that mimic human tutoring, gradually fading as independence grows. This includes algorithmic scaffolding for tasks like writing, problem-solving, simulations, or visual learning analytics interpretation (Maphalala & Ajani, 2025). AI functions as dynamic scaffolding within the ZPD, simulating the more knowledgeable other role with infinite patience and precision. It supports progression from assisted to independent mastery, reducing cognitive load while fostering deeper understanding and enabling "leapfrogging" effects where procedural tasks are offloaded for earlier higher-order engagement (Mutiga et al., 2025). The benefits include decreased cognitive load (e.g., by optimising extraneous load through adaptive guidance and personalization, allowing focus on germane processing) (Meng et al., 2025; Crompton & Burke, 2023), higher engagement via tailored interactions that boost motivation and active participation (Crompton & Burke, 2023; Maphalala & Ajani, 2025), and improved performance in areas like story/spatial learning, STEM, for example., intelligent tutoring systems enhancing conceptual mastery and test scores in maths/science (Xu & Ouyang, 2022; Crompton & Burke, 2023), language (e.g., adaptive tools supporting reading/writing proficiency and comprehension) (Maphalala & Ajani, 2025), and special education (e.g., via visual tools for spatial/story tasks, handwriting recognition/speech-to-text for motor or dyslexic challenges, and personalised aids reducing barriers for neurodevelopmental needs) (Khasawneh & Khasawneh, 2024).

Thirdly, AI can result in improved communication, collaboration, and engagement. AI enhances interaction through adaptive tools (e.g., intelligent tutoring systems, chat-based feedback, gamified platforms, or proactive GenAI agents) that offer instant, targeted responses. This boosts motivation, agency, classroom participation, and collaborative opportunities, even in large or diverse cohorts (Crompton & Burke, 2023). As a cultural tool mediating social processes, AI facilitates collaborative knowledge co-construction, simulating social interactions, providing real-time feedback, and promoting intrinsic motivation via elements like rewards and personalised challenges. It sustains engagement by aligning support with individual needs, leading to greater autonomy, enthusiasm, and long-term comprehension gains (Maphalala & Ajani, 2025).

Finally, there are broader institutional and equity gains. AI democratises access to high-quality, one-on-one-like support, expands immersive experiences (e.g., VR/AR simulations), and aids administrative tasks (freeing educators for deeper interactions). It can accelerate higher-order thinking by offloading procedural tasks, enabling earlier engagement with complex concepts, and particularly benefiting underrepresented or struggling learners through targeted interventions (Bearman et al., 2023). By expanding the ZPD permanently (e.g., "leapfrogging" effect), AI shifts focus from rote procedures to creative, critical, and collective intelligence, promoting equitable, inclusive learning (Mutiga et al., 2025).

These benefits align with a human-centred approach. AI enhances rather than supplants human capabilities, promoting equitable, inclusive, and theoretically grounded integration in higher education.

The risks of AI adoption in HE

While AI offers significant potential when integrated thoughtfully, its adoption in higher education (HE) also presents profound risks that must be critically examined. From a Vygotsky-inspired perspective, unmediated or poorly designed AI can disrupt social constructivism by distorting cultural tool mediation, reinforcing unequal social interactions, or narrowing the zone of proximal development (ZPD) through biased or dehumanised scaffolding (Vygotsky, 1978). Rather than augmenting human mediation, AI may inadvertently replace it, undermine authentic knowledge co-construction, or perpetuate systemic inequities. These risks demand institutional safeguards to ensure AI remains a supportive, equitable cultural tool.

Firstly, algorithmic bias and unfairness represent a core threat. Bias arises systematically from flawed training data, algorithmic design, or human interpretation, leading to discriminatory outcomes that deviate from expected fairness (Ferrara, 2023; Huang, 2023; Kamenskih, 2022; Leta & Vancea, 2023; Stahl & Wright, 2018; Wilson et al., 2017). In higher education contexts, this manifests in admissions systems that disadvantage certain demographic groups, automated grading that penalises non-standard expression, or recommendation engines that limit exposure to diverse perspectives. Fairness in AI requires balancing multiple definitions (e.g., individual vs. group equity) and prioritising context-specific mitigations, yet rapid integration often outpaces such scrutiny. Without deliberate debiasing and ongoing audits, AI risks amplifying existing inequalities, constraining learners' ZPD by providing skewed mediation that favours privileged groups and hinders equitable development.

Secondly, privacy and data protection concerns are heightened by AI's reliance on extensive personal data. Learning analytics, adaptive systems, and cloud-based tools collect vast amounts of student information—behavioural patterns, performance metrics, and even biometric data—raising risks of security breaches, unauthorised misuse, or loss of institutional control (Stahl & Wright, 2018; Floridi et al., 2019; Wilson et al., 2017; Amo Filvá et al., 2021; Huang, 2023). Diverse user competence levels exacerbate vulnerabilities (Kamenskih, 2022), while limited transparency and user control erode trust (Leta & Vancea, 2023). From a Vygotskian view, excessive surveillance can inhibit the social, exploratory interactions essential for authentic mediation within the ZPD, turning learning environments into panoptic spaces that prioritise data extraction over genuine developmental support.

Thirdly, academic dishonesty and integrity erosion have intensified dramatically. Generative AI tools enable effortless production of assessment responses, amplifying pre-existing concerns from contract cheating platforms (Sweeney, 2023; Humble et al., 2024). Since 2023, nearly 17 000 peer-reviewed articles have addressed AI's impact on academic integrity, reflecting widespread academic anxiety. Easy access to free, high-quality AI outputs risks undermining authentic effort, critical thinking, and the social negotiation of knowledge central to Vygotsky's framework. Over-reliance may bypass the ZPD entirely, producing superficial "performance" without internalised mastery and eroding the cultural tools' role in fostering higher psychological processes.

Finally, resistance, commodification, and loss of agency reveal deeper ideological risks. Technology acceptance models partly explain low adoption rates, with resistance tied to perceived threats to professional identity and workload (O'Dea & O'Dea, 2023). Academics who embrace AI are often viewed positively (Pacheco-Mendoza et al., 2023) yet benefits frequently align with neoliberal priorities, namely administrative efficiency for institutions and consumer-like convenience for students, often at the cost of learner agency (Bearman et al., 2023; Preston, 2022).

Utopian narratives overpromise AI as a universal solution, while dystopian fears highlight resource inequality and diminished human control. Critically, institutional support for academics remains underdeveloped, with responsibility individualised rather than systemic. From a Vygotskian lens, this commodification risks transforming education into a transactional rather than socially mediated process, narrowing cultural tool use to efficiency metrics and sidelining collective, emancipatory knowledge construction. These risks underscore the necessity of a human-centred, theoretically grounded approach. AI must be mediated institutionally to preserve authentic social constructivism, equity, and developmental integrity in higher education.

AI and teaching and learning theory: We have paint, but not a solid canvas.

Existing approaches to leveraging artificial intelligence (AI) in higher education (HE) can be broadly categorised into four types: contextual descriptions of HE practices, student-focused pedagogical applications, technical implementations, and technology adoption models (Bearman et al., 2023; Chu et al., 2022). While these contributions highlight AI's potential, they often lack a robust, institution-wide teaching and learning theoretical foundation, limiting their ability to address the holistic nature of HE.

Contextual descriptions emphasise AI's role in specific settings, such as developing countries (Illic et al., 2021; Altememy et al., 2023), or draw on thought leaders and self-reported data to advocate adoption (Nassoura, 2022; Pacheco-Mendoza et al., 2023). Some call for dedicated AI education concepts to reduce uncertainty (Crompton & Burke, 2023) or invoke ideological principles like massification, personalisation (Araiza & Garcia, 2021), and self-regulation (Li et al., 2021; Harati et al., 2021; Menggo et al., 2022). Deliberate design is advocated (Cavanaugh et al., 2020), with optimistic claims that AI may reduce bias in teaching (Altememy et al., 2023; Li et al., 2021). Administrative blueprints, such as George and Wooden's (2023) "AI-centred smart university" model, list components (e.g., intelligent tutoring centre, data-driven curriculum design) around a circular framework. While ambitious, this approach remains largely descriptive, with limited interconnections between components, which are essential for machine learning's data requirements, and omits core elements like disciplinary faculties or graduation processes. It also separates related functions (e.g., tutoring from curriculum design), which contrasts with principles of constructive alignment (Biggs, 1999).

Many approaches prioritise students, focusing on autonomous learning (Li et al., 2021), prior experiences (Welch Bacon & Gaither, 2020), abilities (Alshammari & Qtaish, 2019; Cardenas et al., 2021), or styles (e.g., VARK; Ferguson & Aitken, 2019), despite limited evidence for style-matching benefits (Pashler et al., 2008). Technical work describes applications, computational models, and integration challenges (Bearman et al., 2023; Khosravi et al., 2019; Li et al., 2021), though occasional misinterpretations of learning theories persist.

Technology adoption models dominate conceptual frameworks. The Technology Acceptance Model (TAM) emphasises perceived usefulness and ease of use but has been critiqued for oversimplification and neglecting broader factors like beliefs, risks, comfort levels, and socio-cultural influences (Ghimire & Edwards, 2024; Marikyan & Papagiannidis, 2023; Xue et al., 2024). The Unified Theory of Acceptance and Use of Technology (UTAUT) extends TAM, incorporating moderators like age and experience, yet specialised reviews highlight gaps in higher education-specific applications (Rashid & Ouyang, 2024). The Technological Pedagogical Content Knowledge (TPACK) model integrates technology, pedagogy, and content knowledge effectively for classroom integration but primarily addresses individual instructors rather than institution-wide ecosystems. These models, rooted in technology rather than core teaching and learning principles, fall short for comprehensive AI leveraging in higher education, which requires interconnected institutional components and data flows. Student-centric or technical foci, while valuable, often overlook systemic academic support and ideological implications, such as commodification risks.

Vygotsky's social constructivism provides a stronger foundation, framing AI as a cultural tool mediated through social interaction to expand the zone of proximal development (ZPD), or the space between independent and assisted performance (Vygotsky, 1978, 1929). Unlike adoption models, it emphasises analysing institutional components (e.g., curricula, assessments, administration) and their interrelationships to build a holistic data ecosystem. This approach directly addresses gaps. AI can scaffold authentically across disciplines, mitigate bias through guided mediation, support faculty development, and align with constructive alignment by interconnecting teaching, learning, and research. By grounding AI in human development rather than acceptance or technical integration, Vygotsky's framework enables ethical, equitable, and practical institution-wide adoption.

A model for the adoption of AI in HE: What is the nature and purpose of our canvas and paint?

To address the limitations of existing technology-driven models, we propose a theoretically grounded framework for leveraging artificial intelligence (AI) in higher education, rooted in Vygotsky's social constructivism. Central to this approach is the concept of AI as a cultural tool that mediates higher psychological processes, fundamentally transforming how tasks are understood and performed (Vygotsky, 1929, 1978). Rather than adding AI peripherally, institutions must reconceptualise core functions, namely, knowledge creation (research) and dissemination (teaching)—through systematic analysis of material conditions, historical development, and interrelationships among components.

Vygotsky's dialectical method provides the analytical foundation. Begin with concrete institutional realities, examine each component, and synthesise their interconnections to form a holistic system (Vygotsky, 1978; Mooney, 2013). This contrasts with models like TPACK, which focus primarily on individual instructor knowledge, or TAM/UTAUT, which prioritise user acceptance over pedagogical depth (Ghimire & Edwards, 2024; Rashid & Ouyang, 2024). Historical patterns in higher education, such as replicating traditional lectures in learning management systems (LMS) or online shifts during the pandemic, illustrate resistance to fundamental reconceptualisation, underscoring the need for Vygotsky's tool-mediated transformation.

The central point is to illustrate the transformative role of a cultural tool in elevating psychological and institutional processes. In its simplest form higher education often moves directly from institutional "task" (the core mission of knowledge creation through research and dissemination through teaching, where knowledge and skills are inseparable) to "responses" (existing practices, such as LMS supported delivery, in-person lectures or tutorials, diverse assessment methods like assignments and tests, prescribed textbooks, repositories, campus activities and graduation certification). When a cultural or technological tool such as AI is introduced into this relationship, the movement from task to response is no longer direct. Instead of moving straight from institutional purpose (task) to established practices (response), the process is rerouted through the tool itself. In this way the tool interrupts the direct line, shaping how the task is interpreted and how the response is constructed. The outcome is therefore transformed and not merely improved, creating the possibility of a different response. This transformative role emphasises Vygotsky's key insight that tools do not merely supplement action but fundamentally restructure it, altering both how we conceptualise the task and how we execute it (Vygotsky, 1929, 1978).

Applying this to higher education, AI cannot be treated as an optional add-on. Leveraging AI requires a profound shift. Reconceptualising teaching as dynamic, data-informed scaffolding rather than static delivery. Research as interconnected discovery, and administration as predictive support. Historical examples highlight higher education's resistance to such shifts. The persistence of lecture-based transactions, the mere reproduction of traditional methods in LMS platforms, and the replication of in-person teaching online during the pandemic.

Effective AI integration demands rigorous, dialectical analysis of higher education's material conditions, historical context, and purposes, alongside AI's capabilities (Vygotsky, 1978; Mooney, 2013). Vygotsky's methodology ensures consistency. Examine each institutional component, map their interrelationships, and synthesise a transformed whole. This provides the foundation for the institutional CMS proposed in the following section.

Vygotsky's dialectical historical materialism offers a robust method for analysing human development, adaptable here to leveraging AI in higher education (Vygotsky, 1978; Mooney, 2013). This approach begins with concrete material conditions. These are current higher education practices and AI capabilities in specific institutional contexts, rather than imposing abstract principles. It requires examining historical trajectories (e.g., higher education's evolution from elite to massified systems, AI's shift from rule-based to deep learning) and dialectically analysing individual components alongside their interrelationships to synthesise a transformed whole.

A practical starting point is an AI-enabled institutional content management system (CMS). A comprehensive data ecosystem that pools and interconnects all institutional information to power machine learning (Pierce et al., 2022). Defined as software for storage, indexing, retrieval, archiving, and version control of content assets (as cited in Pierce et al., 2022, p. 194), an institutional CMS extends beyond partial applications. Partial applications include teaching-focused repositories, which face scalability challenges across disciplines (Khosravi et al., 2019). A complete application encompasses administrative functions like admissions, advising, scheduling, and career services (Pierce et al., 2022). Building this CMS dialectically involves mapping material conditions by aggregating existing data (curricula, student records, research outputs, engagement activities) into a unified pool, using scanning/tagging tools for efficiency.

The analysis of each component involves organising by higher education pillars (teaching/learning, research, community engagement) and core elements (e.g., qualifications as primary tags, cascading to modules/outcomes for alignment (Biggs, 1999). The synthesis of inter-relationships links data flows, e.g., student performance informing adaptive teaching, research insights enhancing assessments, or administrative predictions supporting equity. All of these enable AI scaffolding within expanded ZPDs.

This interconnected structure avoids "dumb" repositories by incorporating ethical tagging (e.g., for bias detection/privacy) and faculty input for quality. Implementation requires software development, collaborative data entry, and costing models accounting for training and governance (Pierce et al., 2022). Grounded in Vygotsky's method, the CMS facilitates transformative AI leveraging. Elevating direct practices (e.g., static lectures) to mediated, dynamic processes that address bias, privacy, integrity, and agency concerns institution-wide (Vygotsky, 1929, 1978). Below is a high-level example of what a CMS would look like in an institution. However, the diagram should not be used as merely a template for institutional mapping as this would violate the central importance of context in the Vygotskian model.

Figure 1 presents a conceptual diagram of the proposed institutional Content Management System (CMS) for a higher education institution. The diagram draws from Vygotsky's dialectical approach, showing how analysing components and their interrelationships creates a holistic, AI-enabled data pool. It visualises the CMS as an interconnected ecosystem centred on the student journey (from admission to graduation and beyond). The diagram features a central hub or circle representing the student journey, surrounded by four core functional components, Product, Access, Administration, and Content, connected by bidirectional arrows or lines to show data flows and relationships. These components link to the three traditional pillars of higher education - teaching and learning, research, and community engagement. The overall structure emphasises integration, with qualifications as the primary organising principle.

The Product component represents the "outputs" of the institution, primarily qualifications, degrees, programmes, and curricula. It serves as the central organising principle of the CMS. It includes qualification names, structures, exit-level outcomes, module descriptions, and learning pathways. Products relate to Access because Products inform admissions criteria and enrolment eligibility. Products drive scheduling, resource allocation, and progress tracking (Administration). Products link to specific materials and assessments required for each qualification (Content). Products relate to Pillars because Products directly support teaching/learning (curriculum delivery), research (programme-aligned projects), and community engagement (applied outcomes). Products act as the overarching framework, or the student's "journey" through a specific product (e.g., a bachelor's degree).

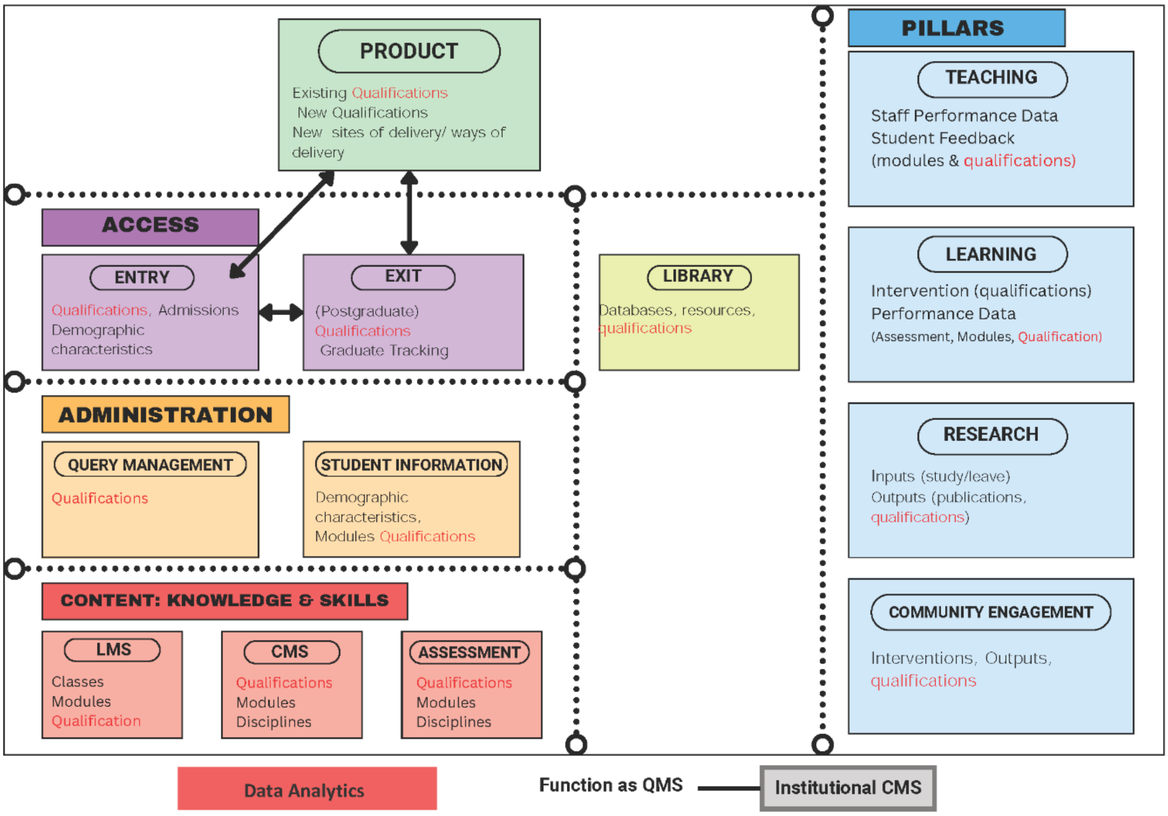

Figure 1: University CMS: Core Functions and Relationships in the Student Journey

Access covers entry and equity mechanisms, ensuring inclusive pathways into the institution. The content in Access is admissions data, applications, scholarships, recognition of prior learning, and enrolment records. Access filters applicants based on qualification requirements (Product). Access feeds into registration, orientation, and initial advising (Administration). Access provides foundational student profiles for personalised learning resources (Content) and promotes equitable teaching/learning access, diverse research participation, and community outreach (Pillars). Access is the entry point in the student journey. The data here initiates personalised AI predictions (e.g., at-risk identification).

Administration is the operational and support functions for smooth institutional running. Administration includes scheduling, academic advising, career services, housing, financial aid, and student support records. Administration aligns timetables and advising with qualification pathways (Product), manages post-admission logistics (Access) and integrates administrative data with learning analytics for holistic views (Content). Administration enables efficient teaching (e.g., class scheduling), research administration (e.g., ethics clearance), and community partnerships. Administration supports student progression and AI uses this data for predictive interventions (e.g., retention alerts).

Content is the repository of knowledge assets and materials and includes lectures, readings, videos, assessments, research outputs, OERs, and engagement activities. Content is mapped directly to modules and outcomes (Product), onboarding materials (Access) and informs advising and career tools (Administration). Content is core to teaching/learning delivery, research dissemination, and community impact. Content is the dynamic "fuel" from which AI draws from this for adaptive scaffolding and personalised pathways.

In summary, bidirectional data flows (arrows/lines) connect all four components, showing interdependence (e.g., a change in Product, like new outcomes, updates Content and Administration automatically). All components feed into a shared view of the individual student's progress, enabling AI to provide holistic support (e.g., linking low engagement in Content to interventions via Administration). Overarching layers or radiating connections show how components support teaching/learning (primary), research (e.g., shared data for projects), and community engagement (e.g., outreach tracking).

Data tagging systems are required for organisation and AI enablement. Hierarchical tagging is required. Primary tagging starts with qualifications (e.g., "Bachelor of Arts – Qualification ID: BA001"), cascading down to exit-level outcomes, modules, and specific items. This ensures constructive alignment (Biggs, 1999). Additional tags by pillar are required (e.g., #TeachingLearning, #Research), function (e.g., #Admissions, #Assessment), format (e.g., #Video, #PDF), ethics (e.g., #SensitiveData for privacy), or bias flags. Tagging enables efficient indexing, retrieval, version control, and reuse. For AI, large, tagged datasets power machine learning (e.g., recommending content based on student performance tags). To implement a tagging system automated scanning tools would be used for initial tagging, with faculty validation for accuracy.

This structure transforms the CMS into an intelligent, interconnected pool, allowing AI to mediate learning dialectically across the institution while addressing risks like bias (via tagged audits) and privacy (via access controls).

Conclusion: Should we buy this piece of art?

Leveraging artificial intelligence (AI) in higher education represents both a profound opportunity and a critical imperative. This conceptual paper argued that AI integration must transcend technology-driven models like TPACK, TAM, and UTAUT, which prioritise acceptance or technical fit over pedagogical depth.

Instead, grounding AI in Vygotsky's social constructivism by treating AI as a cultural tool that mediates development within the zone of proximal development (ZPD) offers a robust, human-centred framework (Vygotsky, 1978, 1929). By dialectically analysing institutional components and their interrelationships, higher education institutions can transform AI from a disruptive force into a mediator of authentic, collaborative knowledge construction.

The benefits include personalised scaffolding at scale, reduced cognitive load, enhanced engagement, and equitable access, all of which demonstrate AI's potential to elevate teaching, learning, research, and administration when ethically mediated. Yet, risks such as algorithmic bias, privacy erosion, academic dishonesty, and neoliberal commodification underscore the dangers of unguided adoption, where AI may distort social mediation or exacerbate inequalities.

The proposed institutional content management system (CMS) that is an interconnected data ecosystem organised by qualifications, pillars, and ethical tagging, provides a practical pathway by pooling resources for AI-enabled prediction, adaptation, and support while mitigating ideological and ethical pitfalls through faculty-led governance and bias audits. Higher education institutions must reject utopian promises and dystopian fears, embracing Vygotsky's call for tool-mediated transformation (Bearman et al., 2023). This requires reconceptualising authority, investing in digital competence, and prioritising systemic over individual responsibility. By implementing theory-informed CMS frameworks, higher education institutions can harness AI to foster inclusive, innovative ecosystems that preserve human agency and advance collective intelligence. Future empirical research—testing CMS models in diverse contexts—will be essential to refine this approach, ensuring AI serves as a scaffold for human flourishing rather than a substitute for it.

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Conflict of interest:

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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