Journal of Inclusive Methodology and Technology in Learning and Teaching
ISSN 2785-5104
Anno 6 n. 4 (2026)

EDIZIONI UNIVERSITARIE ROMANE
editoria scientifica dal 1952

Artificial Intelligence for Self-Determined Learning in Higher Education

Valeria Tamborra[1]

[1] University of Bari; valeria.tamborra@uniba.it

Abstract: Although digital technologies are widely used in higher education for academic support and course design, comprehensive models that evaluate their pedagogical and socio-cultural impact within real-world university settings remain scarce. To address this empirical gap, this paper presents a Design-Based Research project aimed at developing a flexible teaching model designed to promote self-determined learning with the support of Artificial Intelligence. Using a mixed-methods approach that will combine psychometric questionnaires, semi-structured interviews, documentary audits, and the analysis of system interaction logs across multiple disciplines, the study will map student characteristics against faculty teaching competencies. By employing intelligent systems to deliver customised formative feedback, adapted learning materials, and study guidance, this research project seeks to foster autonomous study habits and empower lecturers to orchestrate responsive learning environments.

Keywords: Artificial Intelligence, Higher Education, Self-Determined Learning, Design-Based Research, Learning Analytics.

Copyright: © 2026 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Higher education is currently undergoing major structural changes driven by a more diverse student body and rapid digitalisation, requiring universities to reconfigure conventional instructional models through Learning Management Systems (LMS), data analytics, and Artificial Intelligence (Qolamani & Mohammed, 2023). Within this context, Artificial Intelligence in Education (AIED) offers substantial opportunities to support formative processes and enhance student learning outcomes (Uden & Ching, 2024). However, the rapid expansion of scholarly production on AI in tertiary education leaves open critical questions regarding its long-term effects on classroom pedagogy, cognitive learning processes, and institutional organisation (Batubara et al., 2024). As noted by Alshahrani et al. (2024), a rigorous approach to AIED must integrate pedagogical, ethical, and social dimensions to address the current lack of systematic empirical evaluations concerning its educational value and institutional readiness.

Empirical research shows that classroom assessment and teaching practices directly influence students' approaches to study and the quality of their learning (Marzano et al., 2021). Critical reflections emerging from recent transitions to online and blended instruction have highlighted the need to verify whether traditional transmissive teaching models foster *deep understanding*, defined as the construction of

EDIZIONI UNIVERSITARIE ROMANE
editoria scientifica dal 1952

durable and transferable conceptual representations (Marzano et al., 2021). Promoting deep understanding requires adaptive instructional models centred on learners' cognitive profiles and educational needs (Marzano et al., 2021; Moleka, 2023). Personalising learning processes entails calibrating educational pathways and disciplinary content to the individual characteristics, prior knowledge, and learning preferences of each student, allowing learners to participate actively in constructing knowledge (Fischer et al., 2023; Hardaker & Glenn, 2025). Meta-analytic evidence indicates that personalised education using AI to adapt content to individual proficiency levels produces stronger learning gains than static technology-assisted instruction, provided that clear pedagogical criteria define how personalisation is balanced with collaborative learning pathways (Kucirkova & Gray, 2023).

2. Theoretical Framework

A valuable theoretical contribution to the operationalisation of flexible, student-centred university teaching is offered by *academagogy*, a pedagogical model that integrates elements of pedagogy, andragogy, and heutagogy (self-determined learning) along a dynamic continuum (Addanki et al., 2022). Academagogy allows lecturers to adjust the degree of instructional guidance and scaffolding provided to students according to their maturity and cognitive autonomy, supporting learners in progressing along the Pedagogy, Andragogy, Heutagogy (PAH) continuum towards increasingly self-determined forms of learning, where students autonomously define their learning goals and regulate their epistemic pathways (Addanki et al., 2022).

Supporting university students along the PAH continuum connects directly with the theoretical paradigms describing the integration of Artificial Intelligence in education: *AI-directed*, *AI-supported*, and *AI-empowered* (Heilala et al., 2024; Gunder et al., 2023). Whilst *AI-directed* systems place the learner in a receptive role and *AI-supported* tools offer collaborative assistance without automatically guaranteeing inclusion, instructional design should embrace the *AI-empowered* paradigm, in which Artificial Intelligence acts as an enabling tool that strengthens the decision-making and reflective capacities of both students and lecturers in line with human-centred ethical principles (Heilala et al., 2024; Uden & Ching, 2024; Useche et al., 2022).

In alignment with the *AI-empowered* paradigm, the concept of *student agency* acquires central importance, understood as the student's capacity to act intentionally and autonomously within their learning pathway to develop decision-making and self-regulatory skills (Heilala et al., 2024). In recent higher education scholarship, this construct has been operationalised through *student agency analytics*, a data-informed methodology designed to make explicit how students exercise intentionality, choice, and epistemic control within academic courses, enabling researchers and lecturers to interpret educational data as indicators of active student engagement (Heilala et al., 2024).

2.1. Adaptive pedagogy, formative feedback and human-centred Learning Analytics

In university settings, Artificial Intelligence is widely used both by students for study support, such as summarising content, simplifying complex texts, and building concept maps, and by lecturers, who employ it to design instructional activities, generate teaching materials, and personalise course delivery (Tang, 2024; Alashwal, 2024). Intelligent Tutoring Systems (ITS) and AI-based adaptive platforms analyse learning process data to dynamically adjust instructional content, pacing, and

sequencing to individual student profiles, aligning statistical predictions with cognitive learning theories and bridging the divide between large-scale university lecturing and individualised instruction (Alashwal, 2024; Moleka, 2023; Wang, 2025).

Within personalised teaching models, a central role is played by *feedback*, defined as a communicative process that provides learners with information regarding their performance to support learning improvement and cognitive or metacognitive regulation (Hattie & Timperley, 2007). Feedback thus fulfils a formative and dialogic purpose, promoting self-awareness, self-regulation, and active participation (Hattie & Timperley, 2007; Marzano et al., 2021; Hooda et al., 2022). Artificial Intelligence extends the reach of formative feedback by automating performance monitoring and providing immediate, tailored responses, allowing lecturers to devote greater attention to individual educational relationships (Tang, 2024; Alashwal, 2024).

These analytical functions are closely tied to Learning Analytics (LA) and Educational Data Mining (EDM), which involve collecting, analysing, and interpreting large datasets concerning student interactions and behaviours to detect recurring patterns, identify early signs of cognitive difficulty, and support both faculty teaching design and student self-regulation (Qolamani & Mohammed, 2023; Ahmad et al., 2024; Moleka, 2023). Linking formative feedback with Learning Analytics turns feedback into a dynamic, data-informed instrument (Ghislandi & Raffaghelli, 2015). To address concerns over privacy, algorithmic surveillance, and over-reliance on technology, *Human-Centred Learning Analytics (HCLA)* establish a balanced collaboration between AI systems and human educators, integrating data evidence with lecturers' professional judgement and Technological Pedagogical Content Knowledge (TPACK) competencies (Qolamani & Mohammed, 2023; Dimitriadis et al., 2021).

2.2. Socio-technical activity systems, faculty competencies and literature gaps

Integrating AIED and Learning Analytics into university departments requires a theoretical perspective capable of accounting for the interactions between technological tools and human actors. Cultural-Historical Activity Theory (CHAT) applied to AIED examines the relationships connecting learners, learning tasks, and the broader socio-cultural and institutional context (Uden & Ching, 2024). Within this framework, learning is viewed as a socially mediated activity shaped by cultural tools, interpersonal relationships, institutional rules, and shared academic practices; AIED systems therefore act as mediating artefacts that support collaborative arrangements among lecturers, students, and university institutions (Uden & Ching, 2024).

Managing these socio-technical environments highlights a dual priority for universities: developing diagnostic tools that dynamically assess students' individual cognitive characteristics, and training lecturers to exercise educational leadership focused on content adaptation and student empowerment (Hardaker & Glenn, 2025; Ng et al., 2023). Because many university lecturers still face technical and methodological difficulties in integrating AI applications to support student-centred pedagogy, faculty preparation requires professional development pathways grounded in *Design for Learning*, an iterative and participatory design practice that links pedagogical theory with everyday classroom teaching (Ghislandi & Raffaghelli, 2015; Ng et al., 2023; Jiang, 2025).

Despite the expanding literature on AI in education, significant empirical and theoretical gaps remain. Technological development in AIED is predominantly guided by computer science perspectives with limited input from the learning sciences, resulting in a shortage of empirical studies on its actual pedagogical impact in authentic university courses (Shum & Luckin, 2019; Uden & Ching, 2024). Most studies examine isolated technical features while neglecting the relationship between student cognitive styles, faculty teaching competencies, and departmental infrastructures, as well as the algorithmic opacity and lack of relational sensitivity of commercial AI platforms (Uden & Ching, 2024; Alshahrani et al., 2024; Kucirkova & Gray, 2023). Finally, there is a clear scarcity of iterative Design-Based Research studies that systematically integrate the technological, pedagogical, and socio-cultural dimensions of AIED across diverse academic disciplines (Scott, 2023; Herodotou et al., 2019; Uden & Ching, 2024).

3. Materials and Methods

In response to these gaps, this paper presents a research project that takes as its starting point the following primary research question: how can university teaching be reorganised to align students' educational needs with lecturers' expertise, thereby strengthening the educational relationship and the effectiveness of teaching interventions?

The aim of the project is to develop, test, and validate a teaching model based on the analysis of students' educational needs and learning styles alongside lecturers' disciplinary and pedagogical skills, capitalising on Artificial Intelligence as an enabling tool for personalising study pathways and promoting self-determined learning.

To operationalise this aim, the research project will pursue the following specific objectives:

- To survey and outline the baseline institutional context, specifically: students' cognitive styles, study practices, educational needs, and attendance habits; lecturers' pedagogical skills, needs, and career aspirations; and the infrastructural and regulatory frameworks of degree programmes and departments.
- To develop an adaptive teaching model based on the patterns identified during the context analysis, integrated with a bespoke ecosystem of Artificial Intelligence tools designed to personalise teaching materials, guide study, and deliver tailored feedback to both students and lecturers.
- To test and validate the model through two cycles of classroom experimentation, mixed-methods analysis, and redesign.
- To prototype a theoretical and operational model for the university context that guides the design of adaptive teaching interventions, aligning with the PAH continuum and the principles of responsible, human-centred AIED.

In coherence with the *Design for Learning* approach (Ghislandi & Raffaghelli, 2015), a Design-Based Research (DBR) methodology employing a mixed-methods data collection design will be implemented, in which participating lecturers will engage in *teacher-led inquiry* as reflective educators who observe, evaluate, and refine

classroom interventions (Fischer et al., 2023; Addanki et al., 2022; Scott, 2023; Herodotou et al., 2019). The research project will comprise the following sequential phases:

- Baseline context analysis.
- Development of the teaching model and custom AI ecosystem.
- First experimentation cycle, preceded by faculty training on AI pedagogy and including data collection and impact analysis on lecturers and students.
- Model redesign and second experimentation cycle.
- Analysis of findings and prototype development.

The sample will be selected from the University of Bari, which will serve as the context of investigation. A dimensional sampling technique will be used to select students and lecturers from specific university courses, ensuring appropriate representation across the following dimensions:

- Disciplinary area (economics and law / medical and health sciences / hard sciences / social sciences / humanities and languages).
- Study cycle (bachelor's degree / master's degree / single-cycle master's degree).
- Class size (high-enrolment / low-enrolment courses).

Qualitative and quantitative tools will be utilised to gather the data required for an in-depth investigation of the variables in question and to operationalise both *Human-Centred Learning Analytics* (Dimitriadis et al., 2021) and *Explainable Student Agency Analytics* (Heilala et al., 2024):

- Structured, self-administered psychometric questionnaires for lecturers and students, incorporating an adapted Italian version of the *Index of Learning Styles (ILS)* (Felder & Silverman, 1988) and scales assessing study habits and self-determined learning readiness for students, alongside TPACK and pedagogical competency scales for lecturers (Ng et al., 2023; Jiang, 2025).
- Semi-structured interviews with lecturers and students to explore subjective perceptions, relational dynamics, and perceived feedback utility.
- Standardised checklists for conducting a documentary analysis of the infrastructural and regulatory context of the degree programmes and departments.
- Tracking systems and Learning Analytics (log data) for the quantitative analysis of user-AI system interactions.
- Content analysis of conversational logs (prompt analysis) to qualitatively assess the epistemic and metacognitive nature of the interactions between users and the AI system along the PAH continuum (Addanki et al., 2022; Heilala et al., 2024).

The empirical data gathered during the baseline analysis and monitoring will directly instruct and calibrate the AI ecosystem. Psychometric profiles derived from the adapted ILS questionnaire will initialise the learner model to adjust the format of study materials and scaffolding to each student's cognitive style (Felder & Silverman, 1988; Alashwal, 2024), whilst verified course materials provided by lecturers will be

indexed on the platform. During experimentation, real-time log data and prompt metrics will inform task, process, and self-regulation feedback (Hattie & Timperley, 2007), and aggregated interaction patterns will be displayed on HCLA dashboards to help lecturers adjust classroom teaching (Dimitriadis et al., 2021).

4. Expected Results

Upon completion of the research phases, the following outcomes are expected:

- A descriptive framework detailing the educational needs, study habits, and learning styles of students, categorised by disciplinary area, study cycle, and enrolment numbers, paired with a mapping of faculty competencies and departmental infrastructures.
- A version of the *Index of Learning Styles (ILS)* (Felder & Silverman, 1988) adapted to the Italian university context, which lecturers can employ as a diagnostic tool during the teaching design phase.
- An adaptive teaching response model, grounded in empirical evidence, that will integrate AI tools capable of providing tailored formative feedback to students and lecturers, personalising teaching materials, and offering study guidance.
- Actionable guidelines for teaching design (*Design for Learning*) within the involved courses, fostering a shared reflection on university pedagogy.
- A set of metrics and interaction patterns (*Learning Analytics* and *Explainable Student Agency Analytics*) describing how students and lecturers practically engage with Artificial Intelligence tools in their daily academic routines.

5. Discussion

Interpreting the expected results considering international literature and the project's working hypotheses highlights several theoretical, methodological, and practical implications for experimental pedagogy. From a theoretical standpoint, integrating students' cognitive needs, lecturers' pedagogical expertise, and the analytical and generative capabilities of Artificial Intelligence aims to establish a socio-technical learning ecosystem in which technology serves as an enabling mediating artefact (Uden & Ching, 2024; Alshahrani et al., 2024; Shum & Luckin, 2019). Grounding the proposed model in Activity Theory and the *AI-empowered* paradigm (Heilala et al., 2024; Gunder et al., 2023) is intended to move university instruction beyond passive information reception, orchestrating adaptive feedback mechanisms to foster *deep understanding* (Marzano et al., 2021) and scaffold learners' progression along the PAH continuum towards self-determined learning (Addanki et al., 2022).

From a methodological perspective, correlating subjective stakeholder perceptions, to be captured through psychometric questionnaires and semi-structured interviews, with actual human-machine behavioural traces derived from system logs and conversational prompt analyses will address a recurrent limitation in current AIED research (Batubara et al., 2024; Uden & Ching, 2024). Combining psychometric profiling via the adapted ILS (Felder & Silverman, 1988) with *Explainable Student Agency Analytics* (Heilala et al., 2024) and *Human-Centred Learning Analytics* (Dimitriadis et al., 2021) will provide transparent metrics to evaluate how customised formative feedback (Hattie & Timperley, 2007; Hooda et al., 2022)

supports cognitive self-regulation, offering a sustainable pedagogical solution for reconciling mass enrolment with personalised instruction (Alashwal, 2024; Wang, 2025; Kucirkova & Gray, 2023).

Furthermore, involving lecturers in iterative cycles of professional development, classroom experimentation, and data-informed redesign (*teacher-led inquiry*) will position university educators as reflective designers of learning environments who exercise educational leadership aimed at student empowerment (Ghislandi & Raffaghelli, 2015; Ng et al., 2023; Hardaker & Glenn, 2025; Jiang, 2025). Future research trajectories stemming from this project will include longitudinal studies examining the durability of heutagogical study habits across students' academic and professional transitions, cross-institutional replications, and the exploration of multimodal affective computing. Looking ahead, the iterative nature of this Design-Based Research project across multiple disciplines, study cycles, and class sizes will ensure that the resulting teaching model is both rigorous and adaptable, aspiring to extend beyond the initial context of investigation to lay the groundwork for scalable, ethically responsible AIED practices that foster personalised and self-determined learning pathways.

References

Addanki, K., Holdsworth, J., Hardy, D., & Myers, T. (2022). A preliminary study using academagogy to uncover the problems that block adult online learner engagement. In *Proceedings of the Australasian Computing Education Conference (ACE '22)* (pp. 95–104). ACM. https://doi.org/10.1145/3511861.3511871

Ahmad, K., Iqbal, W., El-Hassan, A., Qadir, J., Benhaddou, D., Ayyash, M., & Al-Fuqaha, A. (2024). Data-driven artificial intelligence in education: A comprehensive review. *IEEE Transactions on Learning Technologies*, 17, 12–31. https://doi.org/10.1109/TLT.2023.3314610

Alashwal, M. (2024). Empowering education through AI: Potential benefits and future implications for instructional pedagogy. *PUPIL: International Journal of Teaching, Education and Learning*, 8(1), 201–212. https://doi.org/10.20319/ictel.2024.201212

Alshahrani, A., Dennehy, D., & Mäntymäki, M. (2024). A social perspective on AI in the higher education system: A semisystematic literature review. *Electronics*, 13(8), 1572. https://doi.org/10.3390/electronics13081572

Batubara, H. S., Jalinus, N., Rizal, F., & Watrianthos, R. (2024). Mapping the frontier: A bibliometric analysis of AI in tertiary education. *International Journal of Learning, Teaching and Educational Research*, 23(10), 62–81. https://doi.org/10.26803/ijlter.23.10.4

Dimitriadis, Y., Martínez-Maldonado, R., & Wiley, K. (2021). Human-centered design principles for actionable learning analytics. In T. Tsiatsos, S. Demetriadis, A. Mikropoulos, & V. Dagdilelis (Eds.), *Research on E-Learning and ICT in Education* (pp. 277–296). Springer. https://doi.org/10.1007/978-3-030-64363-8_15

Felder, R. M., & Silverman, L. K. (1988). Learning and teaching styles in engineering education. *Engineering Education*, 78(7), 674–681.

Fischer, F., Sommerhoff, D., & Keune, A. (2023). Perspectives on learning from the learning sciences. In R. J. Tierney, F. Rizvi, & K. Ercikan (Eds.), *International Encyclopedia of Education* (4th ed., pp. 42–53). Elsevier. https://doi.org/10.1016/B978-0-12-818630-5.14007-2

Ghislandi, P., & Raffaghelli, J. E. (2015). Forward-oriented designing for learning as a means to achieve educational quality. *British Journal of Educational Technology*, 46(3), 560–579. https://doi.org/10.1111/bjet.12257

Gunder, A., Del Casino, V. J., & Vito, M. (2023). Empowering AI: Recontextualizing our pedagogical impact through supportive uses of machine learning. *Ubiquity Proceedings*, 3(1), 1–8.

Hardaker, G., & Glenn, L. E. (2025). Artificial intelligence for personalized learning: A systematic literature review. *International Journal of Information and Learning Technology*, 42(1), 1–18. https://doi.org/10.1108/IJILT-05-2024-0089

Hattie, J., & Timperley, H. (2007). The power of feedback. *Review of Educational Research*, 77(1), 81–112. https://doi.org/10.3102/003465430298487

Heilala, V., Jääskelä, P., Saarela, M., & Kärkkäinen, T. (2024). Adapting teaching and learning in higher education using explainable student agency analytics. In Z. Lv (Ed.), *Principles and Applications of Adaptive Artificial Intelligence* (pp. 20–51). IGI Global. https://doi.org/10.4018/979-8-3693-0230-9.ch002

Herodotou, C., Sharples, M., Gaved, M., Kukulska-Hulme, A., Rienties, B., Scanlon, E., & Whitelock, D. (2019). Innovative pedagogies of the future: An evidence-based selection. *Frontiers in Education*, 4, 113. https://doi.org/10.3389/feduc.2019.00113

Hooda, M., Rana, C., Dahiya, O., Rizwan, A., & Hossain, M. S. (2022). Artificial intelligence for assessment and feedback to enhance student success in higher education. *Mathematical Problems in Engineering*, 2022, 5215722. https://doi.org/10.1155/2022/5215722

Jiang, H. (2025). Digital mindset and sensemaking in AI integration: A study of open education teachers, competence and trust in AI. *SAGE Open*, 15(1), 1–15.

Kucirkova, N., & Gray, S. L. (2023). Beyond personalization: Embracing democratic learning within artificially intelligent systems. *Educational Theory*, 73(4), 569–589. https://doi.org/10.1111/edth.12590

Marzano, A., Miranda, S., & Vegliante, R. (2021). Deep understanding. Control of student understanding in university during distance and face-to-face learning. *Education Sciences & Society*, 12(1), 132–148.

Moleka, P. (2023). Exploring the role of artificial intelligence in Education 6.0: Enhancing personalized learning and adaptive pedagogy. *Preprints*, 2023090562. https://doi.org/10.20944/preprints202309.0562.v1

Ng, D. T. K., Leung, J. K. L., Su, J., Ng, R. C. W., & Chu, S. K. W. (2023). Teachers' AI digital competencies and twenty-first century skills in the post-pandemic world. *Educational Technology Research and Development*, 71(1), 137–161. https://doi.org/10.1007/s11423-023-10203-6

Qolamani, K. I. B., & Mohammed, M. M. (2023). The digital revolution in higher education: Transforming teaching and learning. *Qalamuna: Jurnal Pendidikan, Sosial dan Agama*, 15(2), 837–848. https://doi.org/10.37680/qalamuna.v15i2.3905

Scott, C. (2023). Theoretically rich design thinking: Blended approaches for educational technology workshops. *International Journal of Management and Applied Research*, 10(1), 45–60.

Shum, S. B., & Luckin, R. (2019). Learning analytics and AI: Politics, pedagogy and practices. *British Journal of Educational Technology*, 50(6), 2785–2793. https://doi.org/10.1111/bjet.12880

Tang, A. (2024). Implications of artificial intelligence for teaching and learning. *Acta Pedagogia Asiana*, 3(2), 65–79.

Uden, L., & Ching, G. S. (2024). Activity theory-based ecosystem for artificial intelligence in education (AIED). *International Journal of Research Studies in Education*, 13(5), 41–56. https://doi.org/10.5861/ijrse.2024.2015

Useche, A. C., Galvis, Á. H., & Díaz-Barriga Arceo, F. (2022). Reflexive pedagogy at the heart of educational digital transformation in Latin American higher education institutions. *International Journal of Educational Technology in Higher Education*, 19(1), 62. https://doi.org/10.1186/s41239-022-00365-3

Wang, Y. (2025). The impact of AI teaching on teaching quality. *International Journal of Web-Based Learning and Teaching Technologies*, 20(1), 1–16.