AI-Driven Teaching-Learning in Higher Education – A Conceptual Typology

Anna Tatarczak
Maria Curie-Skłodowska University
Lublin, Poland
anna.tatarczak@umcs.pl

Nuno Escudeiro
GILT, Polytechnic of Porto (ISEP)
Porto, Portugal
nfe@isep.ipp.pt

***Abstract*—The increasing availability of educational data, combined with the rapid advancement of artificial intelligence (AI) methods, is reshaping decision-making processes within higher education institutions. Data-driven approaches facilitate the systematic analysis of student-related data to support prediction, classification, and strategic management. Nevertheless, despite the growing body of research in this domain, the conceptualization of decision-making processes in higher education remains fragmented and insufficiently systematized. The objective of this study is to develop a conceptual typology of decision-making domains in higher education, derived from a structured review of the extant literature. The analysis concentrates on research in educational data mining, learning analytics, and the application of AI in higher education contexts. The findings result in the identification of core decision-making domains associated with academic processes, organizational management, and digital transformation. The proposed typology elucidates the interrelationships among these domains and reveals persistent gaps in the integration of data-driven approaches into institutional decision-making practices. This study contributes to the conceptual development of higher education as a data-driven ecosystem and provides a foundation for subsequent empirical research focused on the prioritization of decision-making areas and the design and implementation of decision support systems.**

Keywords—artificial intelligence, higher education, educational data mining, learning analytics, intelligent systems, decision-making processes, conceptual framework

I. INTRODUCTION

Higher education institutions (HEIs) increasingly rely on large volumes of student, academic, and administrative data, generated through learning management systems, student information systems, and research-reporting platforms [2]. In parallel, methods drawn from artificial intelligence (AI), educational data mining (EDM), and learning analytics (LA) have matured to a point where they can support the extraction of actionable information from these data sources [2], [3]. Together, these developments are reshaping how decisions are made across the higher-education ecosystem, from individual student support to institution-wide strategic planning.

Despite this growth, the literature that examines AI-supported and data-driven decision-making in higher education remains fragmented across several parallel streams. Reviews of multi-criteria decision-making (MCDM) techniques in higher education report that, prior to 2021, no study had systematically mapped the application fields in which such techniques are used [1]. Reviews of artificial neural network (ANN)-based educational data mining similarly report that sustained attention to its open methodological issues remains limited [3]. A substantial body of learning-analytics (LA) reviews documents applications ranging from feedback [8] and learning design [10] to retention interventions [9], yet repeatedly concludes that the evidence for actual improvements in learning outcomes and institutional practice remains thin [7]. Broader reviews of artificial intelligence in education (AIEd) confirm a rapid growth in publication volume [12] but a persistent concentration on teaching-and-learning applications relative to institutional governance [11], [13]. Only recently have systematic reviews turned explicitly to AI-supported governance and decision-making at the institutional level [14], [15]. Taken together, these literatures – spanning MCDM, EDM, learning analytics, AIEd, and institutional governance – address overlapping decision problems without offering a shared conceptual vocabulary for the decision-making domains involved.

This fragmentation motivates the central research question addressed in this paper: How can AI-supported and data-driven decision-making in higher education be conceptually organized across academic processes, organizational and institutional management, and digital transformation?

In response, this paper proposes a conceptual typology that organizes AI-supported and data-driven decision-making in higher education into three interrelated higher-order components: two substantive decision domains – academic processes and organizational and institutional management – and one cross-cutting enabling and governance layer, digital transformation and AI governance. The evidence base comprises twenty-nine scholarly sources [1]-[29], all examined directly: journal articles, systematic reviews and meta-reviews, conference papers, and foundational conceptual publications spanning MCDM, EDM, learning analytics, AIEd, and AI-enabled institutional governance. The paper does not report an empirical study; it offers a conceptual synthesis intended to guide the subsequent empirical prioritization of decision-making areas.

In this study, AI-driven teaching and learning is conceptualized as the core academic layer of a broader higher-education decision ecosystem, in which student- and course-level analytics interact with institutional management and digital-transformation decisions.

The remainder of the paper is organized as follows. Section II establishes the conceptual background distinguishing AI-supported decision-making, educational data mining, and learning analytics. Section III describes the literature-analysis method. Section IV presents the proposed typology, together with a synthesis table and a conceptual figure. Section V discusses the findings, and Sections VI-VIII identify research gaps, implications, and limitations. Section IX concludes the paper.

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II. Conceptual Background

A. AI and Data-Driven Decision-Making in Higher Education

In this paper, AI-supported and data-driven decision-making in higher education is understood as the systematic use of institutional and educational data, analytical methods, and AI techniques to inform decisions at the level of individual students, courses or programmes, or the institution as a whole. This definition follows the broader understanding of data-driven decision-making advanced in the higher-education management literature, where HEIs are described as depending on data collection, storage, and processing across student-information, learning-management, and human-resource systems to support both operational and strategic decisions [2]. Data-driven decision-making is thus distinguished from decision-making based primarily on leadership intuition or unstructured experience [4].

B. Educational Data Mining and Learning Analytics

EDM and LA overlap substantially but differ partly in analytical emphasis and intended use. EDM has traditionally placed greater emphasis on automated discovery, prediction, classification, and computational modelling – including function approximation (regression), pattern recognition (classification), and predictive analytics applied to learner-related data [3]. Artificial neural networks (ANN) are among the EDM techniques most frequently examined for this purpose, given their reported stability in classifying learning behaviour and predicting performance outcomes [3]. LA, by contrast, more explicitly incorporates human interpretation and seeks to transform learner- and context-related data into actionable information for learners, educators, and institutional stakeholders [5], [7]; a review of the LA evidence base distinguishes the two fields not primarily by their techniques but by the role of automated discovery versus human judgement in the resulting decision, noting that EDM more often leads to automated adaptation while LA more often informs a human decision-maker [7]. Accordingly, LA should not be reduced to dashboards or visualization: it encompasses descriptive, predictive, diagnostic, and increasingly prescriptive forms of analytics supporting human decision-making [5], [7]. A broader synthesis of EDM and LA techniques across four dimensions – computer-supported learning, predictive, behavioural, and visualization analytics – confirms that different techniques are suited to different learning problems, but finds that their translation into a coherent, student-focused institutional strategy remains uneven [6]. Even so, a review of 252 LA studies finds only limited evidence that LA improves learning outcomes (9% of studies) or is deployed at scale (6%), despite its high perceived potential [7]; this evidence gap is echoed in reviews of LA-based retention interventions [9] and LA-driven feedback [8] and learning-design practices [10].

C. Academic Analytics as a Bridging Layer

Between the learner-facing focus of EDM/LA and institution-wide governance sits a third, less frequently discussed concept: academic analytics. Foundational work in this area distinguishes academic analytics as the application of business-intelligence methods to education, oriented toward institutional, regional, and system-level decisions concerning resource allocation, retention management, and strategic planning, whereas LA and EDM concentrate more directly on understanding and improving how individual students learn [5], [7]. Rather than forming a linear methodological sequence, EDM, LA, and academic analytics represent overlapping analytical perspectives that operate at different levels and serve partly different decision purposes. Their outputs can nevertheless be organized across three levels of decision-making: micro (individual learner), meso (course, programme, or faculty), and macro (institution or governance system). Academic analytics is therefore treated here as a conceptual bridge between predominantly learner-oriented analytics and institution-level decision support, linking the Academic Processes and Organizational and Institutional Management components developed in Section IV. In the conceptual framework proposed here, outputs generated through EDM and LA may contribute to academic analytics when they are aggregated, contextualized, and used to inform programme-, faculty-, or institution-level decisions [2], [5].

D. From Analytics to Decision Support

The transition from data to institutional action follows a recognizable sequence: data are collected from operational systems, analyzed or used to generate predictions, translated into decision-relevant information, embedded within a decision-support mechanism, and ultimately used to inform institutional action [2], [4]. Intelligent decision support systems (IDSS) occupy the final stages of this sequence: they are described as an integrated approach that combines human-computer interaction with data, models, and structured processes to address uncertainty in decision-making [4]. This paper is concerned specifically with the decision-making stage of this sequence – that is, with the decision-making domains and problems that analytics and AI are reported to support – rather than with the technical properties of the underlying algorithms.

III. Method

This study employed a structured conceptual literature review using a hybrid deductive–inductive coding strategy. The three higher-order components – the two substantive decision domains and the cross-cutting digital-transformation and AI-governance layer – were specified deductively, in accordance with the conceptual structure established in the accepted conference proposal. Within these components, decision problems and recurring lower-level areas were identified inductively from the reviewed literature. This approach preserves consistency with the original conceptual proposition while allowing the lower-level structure of the typology – the twelve analytical, decision-support, and governance areas presented in Section IV – to emerge from the evidence rather than being imposed on it.

Source selection was purposive and concept-driven rather than exhaustive. Sources were retained when they contributed directly to at least one of four analytical purposes: (1) defining AI-, EDM-, LA-, or analytics-supported decision-making in higher education; (2) identifying recurring educational or institutional decision problems; (3) explaining the transition from analytical output to human or organizational action; or (4) addressing institutional adoption, governance, explainability, accountability, or human oversight. Broad reviews were used to map the field, while specialized reviews and selected primary studies were used to deepen and triangulate the categories emerging from the synthesis.

The evidence base comprised three complementary groups of sources, totaling twenty-nine scholarly items, all examined directly. First, broad systematic reviews and meta-reviews were used to map the main research streams and recurring application areas: MCDM techniques in higher education (72 studies through the beginning of 2021) [1]; data-driven decision-making frameworks and tools in HEIs [2]; ANN-based EDM [3]; IDSS in developing-country HEIs (2010–

2022) [4]; EDM/LA techniques (2000–2017, 402 studies) [6]; the LA evidence base (2012–2018, 252 studies) [7]; LA for feedback practices [8]; LA-based interventions (689 records screened, 11 retained) [9]; LA-driven learning-design improvements (49 studies) [10]; three broad AIEd reviews covering 2007–2018 (146 studies) [11], 2016–2022 (138 studies) [12], and a meta-review of 66 secondary AIEd reviews [13]; and two governance-focused systematic reviews of AI-supported decision-making in universities [14], [15]. Second, specialized reviews were used to deepen the analysis of predictive analytics, human-centred AI, explainable AI, and generative-AI decision support: a systematic review of generative-AI applications in LA and decision support (38 studies) [16]; a decade-long systematic review of predictive learning analytics [23]; a systematic review of human-centred LA/AIEd design [24]; and a systematic review of explainable LA/EDM [25]. Third, foundational conceptual papers and selected primary studies were used to examine how analytical outputs are translated into concrete educational and institutional decisions: foundational papers establishing the analytics-to-decision pipeline and the academic-analytics distinction [5], [17], [18]; primary studies on analytics-informed advising, ethical intervention, and learning-design alignment [19]–[22]; and four primary studies on AI-supported strategic decision-making, admissions analytics, and quality assurance, identified within the reference list of [14] [26]–[29]. For each source, the decision problem addressed, the AI or analytical approach used, the reported decision-making level, and the associated findings and limitations were extracted and coded.

Each area in Table I was additionally assigned a literature-support classification, to avoid treating single-source and well-represented categories as equivalent. An area was classified as Established when represented across at least three distinct sources or literature streams; Supported when represented across two; and Emerging when identified primarily by a single source or by very recent, specialized literature. Because some reviews may include overlapping primary studies, this classification should not be interpreted as a formal assessment of evidence independence, nor as an indicator of methodological quality or causal strength; it indicates only the breadth of representation of a category across the reviewed literature, and is treated as provisional pending the expanded systematic search described below.

This analysis should be understood as a structured, evidence-grounded synthesis of existing secondary and primary literature rather than a completed, fully systematic literature review (SLR) in the PRISMA sense. An expanded systematic search of primary studies – covering databases [INSERT DATABASES], conducted on [INSERT SEARCH DATE], and yielding [INSERT NUMBER OF RECORDS] records after screening – is planned as a subsequent step of the internship project and will be used to validate, extend, and where necessary revise the typology and literature-support classifications presented here.

IV. Results: Typology of AI-Driven Decision-Making in Higher Education

The analysis of the twenty-nine reviewed sources supports a typology comprising three interrelated higher-order components: two substantive decision domains and one cross-cutting enabling and governance layer, together comprising twelve lower-level analytical, decision-support, and governance areas summarized in Table I and Fig. 1. As Fig. 1 illustrates, Academic Processes and Organizational and Institutional Management are treated as the two substantive decision domains, while Digital Transformation and AI Governance is treated as a cross-cutting enabling and governance layer rather than a third domain of the same kind: it comprises the infrastructure, data-governance, and oversight conditions under which decisions in the other two domains are made, rather than a distinct set of substantive decisions in its own right.

A. Academic Processes

Academic processes comprise decisions directly connected with students, teaching, and learning. The reviewed literature provides evidence for five recurring decision-making areas within this domain. First, student performance prediction and classification is supported through ANN-based EDM [3] and is consistently identified as one of the most common AIEd application areas, described as “profiling and prediction” [11] or simply “predicting” [12] across broad systematic reviews, with predictive learning analytics receiving dedicated decade-long synthesis in its own right [23]. Second, retention and dropout-risk identification uses grade and enrolment data, together with EDM techniques, to identify at-risk students and trigger academic advising or intervention. This area is well evidenced but also illustrates the field's evaluation gap most sharply: a dedicated review of intervention studies found that only 11 of 689 screened records evaluated intervention effectiveness [9], while the analytics-to-advising pipeline that operationalizes such interventions was established in early design-based work bridging analytics and academic advisors [19], and a widely cited case study documents the ethical dilemmas institutions face once at-risk labels are acted upon [20]. Third, assessment and feedback decisions are supported by LA-based feedback frameworks structured around what data are used, how they are analyzed, why, and for whom [8], alongside automated assessment and evaluation functions reported across broad AIEd reviews [11], [12]. Fourth, personalization and adaptive learning decisions encompass adaptive systems and personalization – reported as the most prevalent thematic focus in a meta-review of AIEd secondary research [13] – intelligent tutoring systems [11], [12], and emerging generative-AI (GenAI) applications, for which a taxonomy of six functional roles and nine categories of decision-support application has recently been proposed [16]. Fifth, course, curriculum, and learning-design decisions remain a substantial application field in the MCDM literature, with AHP the predominant technique [1], and are complemented by a dedicated strand of learning-analytics research that aligns analytics with pedagogical intent [21] and systematically reviews analytics-driven learning design [22]; even so, a review of 49 learning-design studies found that only a third reported actual improvements and just three measured their effectiveness [2], [10].

B. Organizational and Institutional Management

Organizational and institutional management comprises decisions made at programme, faculty, or institutional-management level. The reviewed literature supports three recurring areas. First, admissions and enrolment planning is supported through decision-support tools that draw on data warehouses and multiple institutional data sources to plan student intake, balance student load, and analyze enrolment trends [2], and is reinforced by a recent multi-model analytics system developed specifically to support admissions decision-making [29]. Second, resource allocation and academic planning – concerning the distribution of financial and educational resources and broader strategic planning – are reported in the MCDM literature [1], in research on data-driven institutional decision-making [2], and in recent governance-focused synthesis [14], and are further supported

by primary evidence on machine-learning-assisted strategic decision-making in higher education [26]. Third, quality assurance and risk management emerges specifically from the governance-focused literature: predictive analytics and AI-integrated decision-support systems are reported to support institutional quality monitoring and risk identification [14], [15], and a dedicated framework for integrating AI into institutional quality-assurance processes has recently been proposed [28]. A fourth candidate area, staff selection and performance evaluation, is reported in the MCDM literature through AHP and hybrid MCDM techniques [1]; because it is currently grounded in only one distinct source, it is not retained as a separate area of the typology at this stage, pending confirmation from the planned expanded search.

C. Digital Transformation and AI Governance

As noted above, this component is treated as a cross-cutting enabling and governance layer rather than a third substantive decision domain: it comprises the conditions and infrastructure under which the decisions described for Academic Processes and Organizational and Institutional Management are made, governed, and trusted. The reviewed literature supports four recurring areas within this layer. First, IDSS adoption and institutional readiness is a distinct research concern in the IDSS literature, particularly in developing-country contexts [4], and is echoed in a governance review that identifies leadership commitment and institutional readiness as determinants of successful AI adoption more broadly [14]. Second, analytics infrastructure and data governance covers the integration of data warehouses and online analytical processing (OLAP) to support institution-wide decision-making [4]. Third, AI governance, accountability, and responsible use consolidates several previously separate concerns – the "black-box" character of neural-network models and non-functional quality concerns such as data privacy, security, and interoperability raised by the ANN-based EDM literature [3]; the anticipatory modelling, data-driven coordination, and accountability-oriented sense-making mechanisms through which institutions embed AI into decision routines [15]; the institutional readiness, leadership commitment, and bias-, privacy-, and transparency-related governance frameworks stressed by public-university governance research [14]; the explicit call for increased ethics, methodological rigour, and contextual sensitivity issued by the most comprehensive AIEd meta-review to date [13]; a dedicated systematic review of explainable-AI methods for LA and EDM, which finds that evaluation metrics for the quality of AI explanations remain underdeveloped [25]; and primary work on verifying the correctness of machine-learning-based institutional decisions [27]. Fourth, and distinct from the preceding accountability-oriented area, human–AI decision-making and oversight addresses how automated discovery is combined with human judgement in the decision itself, rather than how the system is governed after the fact: the LA literature identifies human judgement as the defining feature that distinguishes LA from purely automated EDM [7]; governance research describes AI-enabled governance as reshaping information flows and decision routines rather than simply automating them [15]; and the generative-AI literature explicitly recommends that, in high-stakes decisions, GenAI should assist rather than replace professional judgement [16].

The two substantive domains are conceptually linked through this enabling layer rather than being independent of one another. Fig. 1 represents this schematically: analytical information generated at the level of individual students (academic processes) and programme- or institution-level management decisions (organizational and institutional management) are conceptually linked through what this paper terms a Human–AI Decision Interface – the point at which algorithmic outputs are interpreted, challenged, supplemented, or approved by human decision-makers before institutional action is taken – with the digital-transformation and AI-governance layer providing the infrastructure, governance, and oversight conditions intended to support trustworthy human–AI decision-making. The Human–AI Decision Interface is introduced here as a conceptual construct rather than as an established model from the literature; it synthesizes recurring evidence on human judgement, explainability, accountability, and human oversight across the reviewed research streams.

TABLE I. TYPOLOGY OF AI-SUPPORTED AND DATA-DRIVEN DECISION-MAKING DOMAINS IN HIGHER EDUCATION

Main domain	Framework area	Typical decision problem	AI / analytical approach	Decision level	Literature support	Repr. lit.
Academic Processes	Student performance prediction & classification	Predicting grades/exam outcomes; student profiling	ANN; supervised ML; predictive analytics	Individual student	Established	[3], [11], [12], [23]
	Retention & dropout-risk identification	Identifying at-risk students; intervention triggers	ANN-based EDM; predictive LA interventions	Individual student	Established	[2], [3], [9], [19], [20]
	Assessment and feedback decisions	Automated assessment; personalized, LA-based feedback	LA feedback frameworks (what/how/why/for whom); automated evaluation	Individual student / course	Established	[8], [11], [12]
	Personalization & adaptive learning decisions	Adaptive learning paths; intelligent tutoring; GenAI-based support	Adaptive/personalization systems; ITS; GenAI/LLM decision support	Individual student / course	Established	[11]–[13], [16]
	Course, curriculum & learning-design decisions	Course recommendation; curriculum analysis; redesigning learning activities and course structures	MCDM; recommendation methods; LA-driven curriculum and learning-design analytics	Course / class	Established	[1], [2], [10], [21], [22]
Organizational & Institutional Mgmt.	Admissions & enrolment planning	Capacity planning; enrolment-trend forecasting; admissions analytics	Data-warehouse-based DSS; multi-model admissions analytics	Applicant / institution	Supported	[2], [29]
	Resource allocation & academic planning	Distribution of financial/educational resources; strategic academic planning	MCDM source selection; conceptual IDSS models; ML-based strategic decision support	Institution	Established	[1], [2], [14], [26]

	Quality assurance & risk management	Institutional quality monitoring; operational/academic risk identification	Predictive analytics; AI-integrated decision-support systems; AI-based QA frameworks	Institution	Established	[14], [15], [28]
Digital Transformation and AI Governance	IDSS adoption & institutional readiness	Adoption/implementation of decision-support tools	IDSS adoption frameworks	Institution	Supported	[4], [14]
	Analytics infrastructure & data governance	Data-warehouse / OLAP integration; institutional data-system integration	Data warehousing; OLAP	Institution / ecosystem	Supported	[2], [4]
	AI governance, accountability & responsible use	Addressing black-box, privacy, security, bias, accountability & correctness concerns	ANN quality-assurance methods; explainable-AI (XAI) methods; anticipatory modelling; accountability-oriented sense-making; ML-correctness verification	Institution / ecosystem	Established	[3], [13]–[15], [25], [27]
	Human–AI decision-making & oversight	Balancing automated discovery with human judgement in high-stakes decisions	Human-in-the-loop decision routines; GenAI-assists-not-replaces models	Individual → institution	Supported	[7], [15], [16]

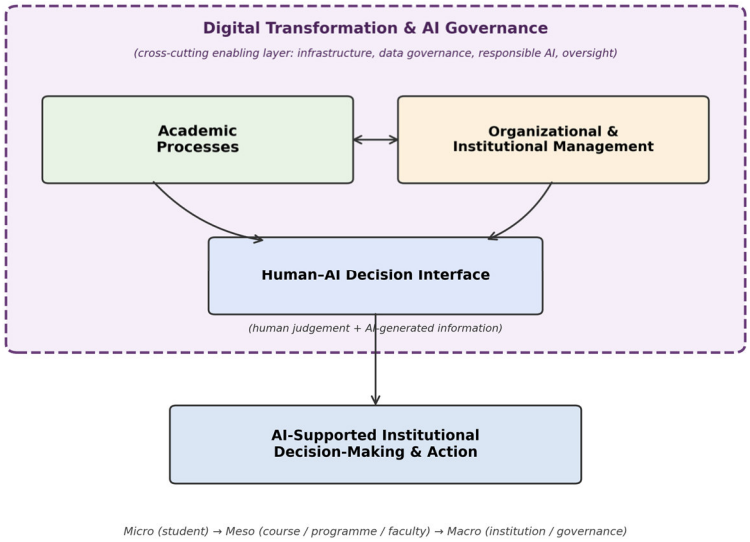


Fig. 1. Conceptual framework linking AI/educational data to the two substantive decision domains and the cross-cutting Digital Transformation and AI Governance layer, via the Human–AI Decision Interface, to institutional decision-making.

V. Discussion

The expanded evidence base confirms that academic-process applications – particularly student performance prediction, assessment, and adaptive learning support – remain the most extensively researched area: broad AIEd reviews consistently identify profiling/prediction and adaptive personalization as dominant themes [11]–[13], and the learning-analytics literature alone spans more than ten dedicated sources [6]–[10], [19]–[25]. At the same time, the inclusion of two governance-focused systematic reviews and associated primary studies [14], [15], [26]–[29] substantially strengthens the evidence available for organizational and institutional management, and motivates treating digital transformation and AI governance as a cross-cutting enabling layer rather than a third, separately evidenced domain (Section IV). These sources report that AI adoption in universities concentrates in strategic, administrative, and risk-related governance functions, supported by anticipatory modelling and data-driven coordination mechanisms [15], and that successful implementation depends on institutional readiness, leadership commitment, and ethical governance frameworks [14].

Even with this stronger evidence base, a consistent imbalance persists. The synthesis reveals what this paper terms an application–evaluation gap across the higher-education AI decision ecosystem: applications are reported much more frequently than their effects on decisions, outcomes, or institutional processes are rigorously evaluated. In the academic-processes domain, only 9% of reviewed LA studies demonstrate improved learning outcomes and only 6% report wide deployment [7]; of 689 records screened for LA-intervention effectiveness, only 11 studies actually evaluated it [9]; and of 49 studies on LA-driven learning-design improvement, only a third reported actual improvements and just three measured effectiveness [10]. In the organizational and digital-transformation components, operational efficiency and predictive accuracy are reported far more often than transparency, accountability, trust, equity, or workload effects [15], and the evaluation of AI-explanation quality itself remains underdeveloped [25]. Taken together, these findings suggest that the current evidence gap concerns not only the breadth of AI applications reported in higher education, but more importantly the limited evaluation of their consequences for actual decisions, educational outcomes, and institutional processes.

A second, equally important pattern is what this synthesis conceptualizes as a vertical integration gap: limited evidence of explicit mechanisms connecting micro-level learner analytics with meso-level academic management and macro-level institutional governance. Even the governance-focused reviews describe AI-enabled governance as operating at strategic, administrative, and risk-related levels without an explicit account of how student-level analytical output feeds

into those higher-level decision processes [14], [15]; no such explicitly integrated architecture was identified within the present evidence base. The academic-analytics concept introduced in Section II.C and the Human–AI Decision Interface positioned at the centre of Fig. 1 are proposed as conceptual mechanisms through which such vertical integration could be examined and operationalized in future research. This is consistent with the fragmentation identified in Section I and supports the conceptual, rather than purely descriptive, ambition of the typology proposed here.

Finally, the concerns raised regarding the "black-box" character of neural-network models [3], together with data-privacy, security, algorithmic-bias, and transparency issues raised in the governance literature [14], [15], the explicit call for increased ethics, collaboration, and rigour issued by the most comprehensive AIEd meta-review to date [13], and the finding that evaluation metrics for AI explanations remain underdeveloped [25], together indicate that human oversight and responsible use of AI are central, rather than peripheral, considerations for the digital-transformation layer. The emergence of generative AI as a further layer of decision-support capability, which the literature explicitly frames as something that should assist rather than replace professional judgement [16], is likely to intensify rather than resolve these concerns, reinforcing human–AI decision-making as a distinct area of the typology (Table I) and as an open area for future research (see Section VI).

VI. Research Gaps

The gaps identified through this analysis are organized into four higher-level categories.

Evidence gap. Reported applications substantially outnumber evaluated outcomes across the higher-education AI decision ecosystem. Reviews of learning-analytics interventions [9], feedback practices [8], and learning-design improvements [10] each report that only a small fraction of identified studies actually evaluate outcomes, echoing the broader finding that only 9% of reviewed LA studies demonstrate improved learning outcomes [7].

Integration gap. No explicitly integrated mechanism was identified in the present evidence base linking micro-level (student) analytics to meso-level (course/programme/faculty) and macro-level (institutional governance) decision-making, despite governance research explicitly describing AI-enabled governance as reshaping information flows and decision routines across levels [15].

Governance and accountability gap. Transparency, accountability, trust, equity, explainability, and human oversight remain less extensively evaluated than operational efficiency and predictive performance [14], [15], [25].

Validation gap. No empirically validated and prioritized taxonomy covering the full range of AI-supported decision-making areas examined in this study was identified within the present evidence base; existing typologies, including the one proposed in this paper, remain conceptual rather than empirically validated. This gap directly motivates the expert-based prioritization exercise planned as a subsequent stage of the present research.

VII. Implications

A. Theoretical Implications

The theoretical contribution of the proposed framework is threefold. First, it integrates previously fragmented research on learner-oriented analytics, institutional decision support, and AI governance within a common decision-oriented structure. Second, it positions academic analytics as a bridging concept between micro-level educational analytics and meso- and macro-level institutional decision-making. Third, it identifies two cross-cutting weaknesses in the current evidence base: the application–evaluation gap and the vertical integration gap.

B. Practical Implications

For university managers, academic leaders, and programme coordinators, the typology offers a structured overview of where AI and data-driven approaches are currently reported to support decisions, which may assist in identifying under-served decision areas within their own institutions. For designers of institutional decision-support systems and educational-technology developers, the typology highlights the distinction between tools oriented toward individual student support and tools oriented toward institutional governance, and the Human–AI Decision Interface concept (Fig. 1) points to a concrete design implication: decision-support systems should be designed to expose analytical outputs for human review rather than to automate decisions outright, particularly where AI outputs inform high-stakes decisions concerning student progression, admissions, resource allocation, or institutional risk.

VIII. Limitations and Future Research

This study has several limitations. The evidence base currently comprises twenty-nine scholarly sources, all examined directly, combining systematic reviews and meta-reviews with foundational conceptual papers and primary studies identified within their reference lists. The typology should therefore be read as a structured conceptual synthesis rather than the result of a completed, fully systematic literature review of primary studies; source selection was purposive and concept-driven (Section III) rather than exhaustive. An expanded systematic search, following PRISMA is planned to extend and validate the categories and literature-support classifications proposed here, and to reassess the candidate staff-selection-and-performance-evaluation area currently excluded from Table I for insufficient distinct support. In addition, the typology is conceptual rather than empirically validated: it has not yet been assessed by domain experts, and category boundaries – particularly across the digital-transformation layer – may overlap in practice, a risk reinforced by the observation that governance mechanisms such as anticipatory modelling and data-driven coordination [15] span multiple areas simultaneously. The evidence specifically concerning IDSS adoption determinants also remains concentrated in a small number of national contexts, particularly developing countries, which limits the contextual generalizability of that area [4]. Finally, given the pace of development in AI methods – illustrated by the very recent emergence of generative-AI applications in this literature [16] – categories associated with digital transformation in particular may require periodic revision.

Future research should empirically validate and prioritize the proposed framework areas through structured expert elicitation. Depending on the final number and hierarchy of criteria, this may involve methods such as the Analytic Hierarchy Process (AHP) – one of the most frequently applied MCDM techniques in higher-education decision problems specifically [1] – the Best–Worst Method, or other suitable multi-criteria prioritization techniques. Such an evaluation would allow the relative importance of the identified decision-making areas to be established empirically, complementing the conceptual contribution of the present paper, and would

inform the subsequent design of decision-support frameworks – including an implemented Human–AI Decision Interface – for institutional implementation.

IX. Conclusion

This paper addressed the fragmentation of research on AI-supported and data-driven decision-making in higher education by developing a conceptual typology grounded in twenty-nine scholarly sources spanning MCDM, EDM, learning analytics, AIEd, and AI-enabled institutional governance. The analysis identifies two substantive decision domains – Academic Processes and Organizational and Institutional Management – embedded within a cross-cutting Digital Transformation and AI Governance layer. Together, these components comprise twelve analytical, decision-support, and governance areas. Beyond the typology itself, the analysis surfaces two cross-domain findings: an application–evaluation gap, whereby applications are reported far more often than their outcomes are measured, and a vertical integration gap, reflected in the limited evidence identified for explicit mechanisms connecting student-level analytics with institutional governance. The conceptual contribution of this paper lies in organizing these disparate literatures into a shared classification framework and in naming these two gaps; its practical relevance lies in supporting the identification of decision areas that may benefit from further data-driven and AI-based support, and from more rigorous outcome evaluation. Future work will extend the underlying literature base through a systematic search of primary studies and will subject the resulting typology to empirical, expert-based prioritization.

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