

Generative AI for Data-Informed Educational Decision-Making: A Systematic Review and Framework

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Abstract—Generative artificial intelligence (GenAI) is creating new possibilities for data-informed decision-making in higher education, yet how it translates educational data into actionable decisions for different stakeholders remains undertheorised. This study reports a PRISMA-guided systematic review of 38 peer-reviewed empirical studies addressing three questions: what educational decisions GenAI supports in higher education (RQ1); how educational data and GenAI capabilities enable those decisions (RQ2); and what framework explains GenAI-driven educational decision-making (RQ3). Across the 38 studies, eight decision categories are identified inductively and organised into micro (learner-facing), meso (instructor and program), and macro (institutional) levels. Five enabling GenAI capabilities (natural language generation, behavioural and semantic analysis, multimodal processing, synthetic data generation, and conversational analytics) are mapped to each category. Synthesising these findings, this study proposes the GenAI-Driven Educational Decision-Making (GDEDM) framework: a four-layer model connecting educational data sources, GenAI capabilities, educational decision levels, and governance. The evidence reveals important cross-level patterns, divergences, and research gaps, exposing a critical governance gap between rapidly advancing GenAI capabilities and lagging institutional safeguards. The GDEDM framework offers researchers, practitioners, and policymakers a coherent, evidence-grounded basis for responsible GenAI deployment in higher education.

Keywords—Educational decision-making; generative artificial intelligence; higher education; data-informed decisions; large language models; systematic review

I. INTRODUCTION

Higher education institutions have invested in data-driven approaches to support a wide range of operational goals, including identifying at-risk students, personalising academic pathways, evaluating teaching effectiveness, and informing institutional resource allocation [1]. Yet translating educational data into timely, actionable decisions for the right stakeholders has remained a persistent challenge.

The emergence of generative artificial intelligence (GenAI), which encompasses large language models (LLMs) such as GPT-4, open-source models including Llama and ERNIE Bot,

retrieval-augmented generation (RAG) systems, and generative adversarial networks (GANs), has significantly expanded what is technically possible in this space [2], [3], [4]. Unlike traditional machine learning approaches that predict or classify based on structured input, GenAI systems can generate natural language, synthesise insights from complex data, and support multimodal analysis [4]. These capabilities position GenAI as a bridge between educational data and decision-making, enabling systems to move beyond producing analytical outputs toward supporting educational decisions for students, instructors, and administrators [5], [6].

Early data-informed decision support in higher education relied on machine learning models for academic outcome prediction, including identifying at-risk students, forecasting grades, and modelling dropout risk [7]. These systems demonstrated the value of multi-feature models integrating behavioural, academic, and socioeconomic variables, but their outputs, such as probability scores and classification results, required considerable human expertise to translate into practical action.

The emergence of LLMs changed what AI-generated educational outputs look like: where predictive systems produce numbers, GenAI systems produce text, recommendations, and dialogues that function as decision artifacts in themselves [3]. Standards-based interoperable architectures combining multi-agent systems, xAPI trace collection, and LTI delivery have further shown how such GenAI decision outputs can be embedded within institutional learning management ecosystems at scale [2]. Yet despite this progress, the field lacks a comprehensive, decision-centred understanding of what GenAI supports across the full spectrum of higher education stakeholders and organisational levels.

Most existing reviews organise findings by model type, analytical technique, or isolated function (e.g., focusing on predictive tasks [8], dashboard applications [9], human-centered design [10], or explainability [11]) rather than by the educational decisions GenAI enables or the governance conditions required to make those decisions responsible. The present study addresses this gap through a systematic review of 38 empirical studies guided by three research questions:

- RQ1: What educational decisions are supported by GenAI in higher education?
- RQ2: How do educational data and GenAI capabilities support these decisions?
- RQ3: What framework can explain GenAI-driven educational decision-making in higher education?

The study makes three original contributions. First, a decision-centric synthesis of 38 empirical studies organised around eight inductively derived decision categories that provide an outcome-focused perspective on how GenAI supports educational decision-making. Second, a three-level decision taxonomy (micro, meso, and macro) grounded entirely in the empirical evidence. Third, the GDEDM framework: a four-layer, governance-inclusive model linking educational data sources, GenAI capabilities, educational decision levels, and responsible AI governance to support both scholarly understanding and institutional deployment.

II. METHODOLOGY

A. Search Strategy and Inclusion Criteria

Electronic searches were completed on March 6, 2026 across Scopus, Web of Science, and IEEE Xplore. The search string combined GenAI terms ("generative artificial intelligence" OR "Generative AI" OR "large language model*" OR LLM OR ChatGPT OR GPT) with educational data and decision terms ("learning analytics" OR "educational decision" OR "educational data mining" OR "student analytics") and higher

education qualifiers ("higher education" OR universit* OR college OR "tertiary education" OR undergraduate* OR postgraduate*). Backward and forward citation snowballing supplemented database retrieval.

Studies were included if they: (IC1) employed a GenAI technique, such as a large language model or generative adversarial network; (IC2) applied it within a learning analytics (LA) workflow; (IC3) were conducted in a higher education context; (IC4) were published in a peer-reviewed journal or conference proceeding; and (IC5) reported original empirical research. A study was considered to involve educational data or LA workflow if it used learner-related data for analysis, modelling, or interpretation to inform understanding or support decision-making in an educational context [12], [13].

Following deduplication, 244 records were screened by title and abstract, of which 35 progressed to full-text review and 24 met the eligibility criteria. Citation snowballing identified 14 additional eligible studies, yielding a final corpus of 38 studies. The main exclusion reasons were absence of GenAI-enhanced LA (EC2, $n = 121$), non-empirical design (EC6, $n = 51$), absent GenAI application (EC1, $n = 34$), non-higher education setting (EC3, $n = 7$), and non-peer-reviewed source (EC4, $n = 3$). Some records met multiple criteria. Two reviewers independently screened the records, resolving disagreements through discussion and consensus, particularly regarding the presence of a learning analytics workflow and empirical evidence. The complete selection process is presented in Fig. 1.

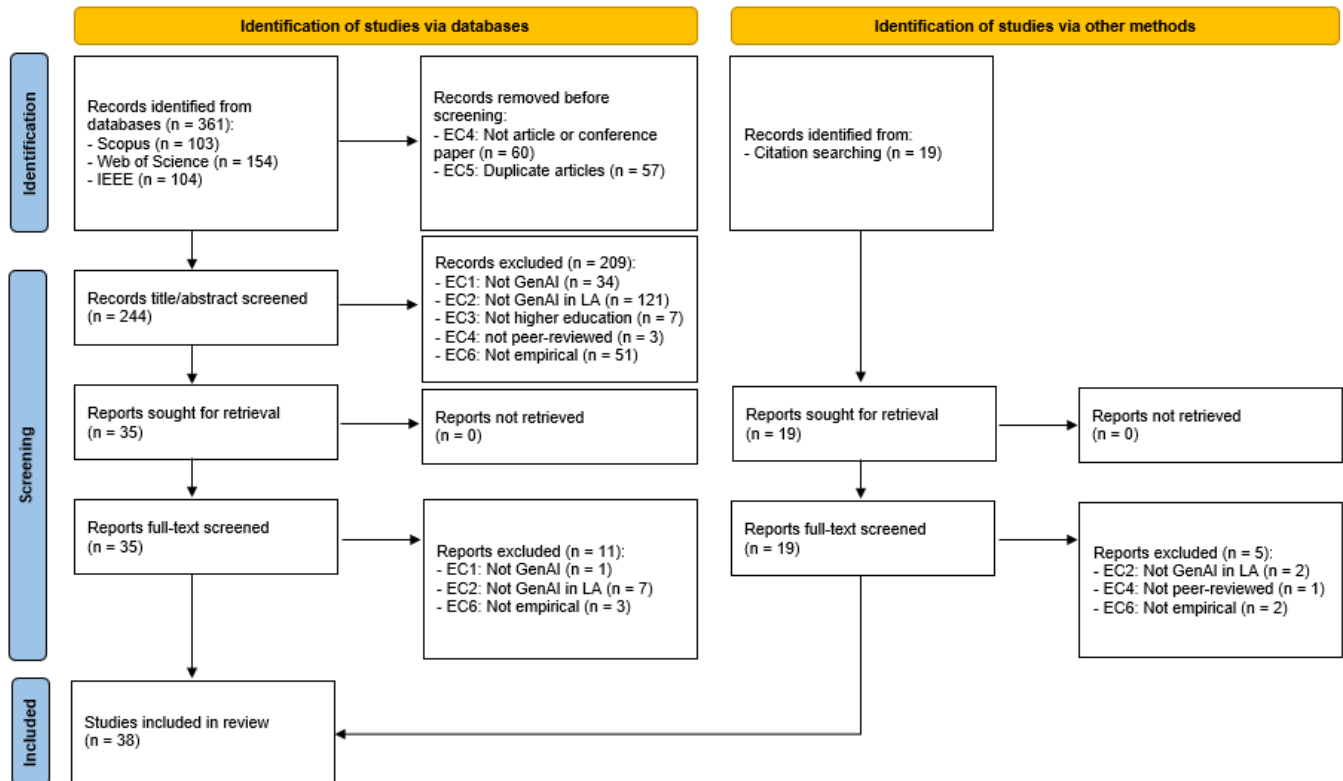


Fig. 1. PRISMA 2020 flow diagram of the article selection process.

B. Data Extraction and Analytical Approach

A structured extraction form captured the GenAI models, educational data sources, stakeholders served, educational decision types, and the GenAI capabilities enabling those decisions. The decision categories were derived inductively. For each study, the decision output was identified and grouped with functionally similar outputs across other studies. Categories were iteratively refined until each was conceptually distinct.

The eight resulting categories were then organised into three decision levels based on stakeholder scope and systemic consequence. Similarly, GenAI capabilities were identified by examining the primary role each GenAI technique performed within the learning analytics workflow. Functionally similar capabilities were grouped and iteratively refined into five overarching categories representing how GenAI enabled educational decision-making across the reviewed studies. Data extraction was performed by the first author and verified by a co-author, with discrepancies resolved through discussion.

Study quality was assessed using the Quality Assessment with Diverse Studies (QuADS) tool [14], a 13-item appraisal instrument suited to the heterogeneous mix of system evaluations, case studies, and user studies in the corpus. The first author appraised each included study across all 13 items, with total scores ranging from 24 to 38 out of 39, indicating generally adequate methodological quality. Quality appraisal informed the depth of synthesis and confidence in specific findings.

III. RESULTS

A. Educational Decisions Supported by GenAI (RQ1)

The synthesis of the 38 studies identified eight educational decision categories supported by GenAI in higher education. These categories were organised into three decision levels: micro (learner-facing), meso (instructor- and program-level), and macro (institutional). Table I maps the decision categories to the GenAI technologies reported in the reviewed studies. Studies employing multiple technologies appear in more than one technology column. This section introduces the decision categories and associated technology patterns, while the subsequent RQ2 section examines how educational data and GenAI capabilities enable these decisions.

1) *Micro-level decision categories*: Four categories operate at the individual learner level. Feedback and Assessment Support is the most frequently studied category in the corpus ($n = 8$) and one of the broadest in technology coverage, supported by GPT-family models, open-source LLMs, unspecified LLMs, and RAG systems. This category focuses on assessment-related decisions through personalised feedback, formative assessment, rubric-based evaluation, and other feedback mechanisms that support learner improvement. The prominence of Feedback and Assessment Support may reflect the growing demand for scalable assessment support and personalised feedback in higher education.

TABLE I. EDUCATIONAL DECISION CATEGORIES AND SUPPORTING GENAI TECHNOLOGIES

Decision Level	Decision Category	GPT-4/4o (ChatGPT)	Open-source LLMs (Llama, DeepSeek, ERNIE)	Unspecified LLMs	RAG Systems	Multimodal LLMs	GANs	Other Generative Models (TVAE, Gaussian Copula, DALL-E)	SQL / NL Query Agents	n
Micro	Feedback and Assessment Support	[15], [16], [17], [18], [19], [20]	[15]	[21]	[22]					8
	Learning Pathway Personalisation	[23], [24], [25], [26]			[22]	[23], [25]				5
	Academic Guidance and Advising	[6], [27], [28], [29]						[29]		4
Meso	Instructional Design Support	[25], [30], [31], [32]	[30], [31], [33]			[25]				5
	Collaborative Learning Analytics	[23], [34], [35]	[34], [36]	[37]		[38]				6
	Analytics Interpretation and Sensemaking	[5], [18], [39], [40]			[39], [41]	[39], [41]			[5], [40]	5
Macro	Early Warning and Intervention	[26], [42], [43], [44]	[45]				[46], [47]	[44]		7
	Strategic Institutional Planning	[5], [27], [29], [40], [48]	[45], [48]					[29]	[5], [40], [49]	7
	Total unique studies per technology	27	8	2	3	5	2	3	3	

2) *Learning pathway personalisation* ($n = 5$) supports decisions about adapting learning experiences, content sequencing, and instructional pathways to individual learner needs. Unlike Feedback and Assessment Support, which evaluates completed learning activities and provides formative feedback, this category focuses on adapting future learning

experiences to individual learner needs. It exhibits considerable technological diversity, incorporating GPT-family models, RAG systems, and multimodal LLMs. Among the reviewed studies, it is the only micro-level category incorporating multimodal LLMs, suggesting growing interest in using diverse learner inputs to support personalised learning experiences.

Academic Guidance and Advising (n=4) supports decisions concerning course selection, programme planning, and academic progression. Whereas Learning Pathway Personalisation focuses on adaptation within learning environments, advising applications address broader academic choices that shape learners' educational trajectories. The category relies predominantly on GPT-family models, with only one study reporting the use of another generative approach (DALL-E) [29]. Its relatively narrow technology profile suggests that a limited range of GenAI approaches has been explored for advising applications in the reviewed studies. Collectively, the three micro-level categories demonstrate the central role of large language models in supporting learner-facing educational decisions, while highlighting distinct forms of decision support ranging from feedback to personalisation and advising.

3) *Meso-level decision categories*: Three categories serve instructors and program teams. Collaborative Learning Analytics (n=6) supports decisions related to monitoring, evaluating, and facilitating collaborative learning activities. It is the largest meso-level category and exhibits substantial technological diversity, combining GPT-family models, open-source LLMs, multimodal LLMs, and unspecified LLM-based agents across the reviewed studies. This technological diversity may reflect the complexity of collaborative learning, which often involves interactions captured through multiple modalities, including text, video, and behavioural traces [38]. [38]

Instructional Design Support (n=5) supports curriculum improvement, course redesign, and instructional planning. Whereas Collaborative Learning Analytics focuses on understanding learner interactions, this category focuses on modifying the learning environment through evidence-informed instructional decisions. GPT-family models, open-source LLMs, and multimodal LLMs are the primary technologies reported in this category.

Analytics Interpretation and Sensemaking (n=5) focuses on supporting stakeholders in interpreting and acting on learning analytics outputs. Rather than generating new instructional recommendations, its primary role is to help stakeholders interpret and act upon existing analytical findings. Among the reviewed studies, it is the only meso-level category incorporating Structured Query Language (SQL) and natural-language query agents and one of only three categories employing Retrieval-Augmented Generation (RAG) systems. This category highlights the role of GenAI in bridging the gap between learning analytics outputs and their practical use in educational decision-making.

4) *Macro-level decision categories*: Two categories operate at the institutional level. Early Warning and Intervention (n = 7) supports decisions related to identifying at-risk students and initiating timely interventions through institution-wide monitoring and intervention strategies. It incorporates a distinctive combination of GPT-family models, graph neural networks (GNNs), GAN-based approaches, and other generative models, reflecting the use of complementary

AI techniques to support institution-wide risk identification and intervention.

Strategic Institutional Planning (n = 7) supports institution-wide strategic and operational decisions related to student success, enrolment management, resource allocation, and organisational performance. Whereas Early Warning and Intervention focuses on identifying students requiring timely support, Strategic Institutional Planning focuses on informing broader institutional planning and management decisions. Its technology profile is characterised by GPT-family models, SQL-based systems, natural-language query agents, and other generative models, highlighting the role of conversational access to institutional data in supporting evidence-informed organisational decision-making.

Together, these macro-level categories illustrate how GenAI supports complementary forms of institutional decision-making: Early Warning and Intervention focuses on identifying and responding to student risk, whereas Strategic Institutional Planning supports broader organisational planning and management. Compared with the learner- and programme-focused categories, macro-level applications rely more heavily on institution-wide educational data and support decisions with broader organisational scope and consequences.

5) *Technology distribution and structural gaps*: GPT-family models appear across all eight decision categories and are employed across 27 of 38 studies, indicating their position as the dominant and most widely adopted technology in the current GenAI decision-support landscape. Open-source large language models (LLMs) (8 studies) appear across several educational decision categories, often serving as privacy-conscious or locally deployable alternatives to proprietary GPT-family models. Retrieval-Augmented Generation (RAG) systems and multimodal large language models (MLLMs) (3 and 5 studies, respectively) occupy more specialised roles, with RAG supporting knowledge-grounded applications and MLLMs concentrated in contexts involving multimodal educational data. Other generative models, including TVAE, Gaussian Copula, and DALL-E, appear in three studies, supporting synthetic data generation and complementary generative tasks. GAN-based models are identified within Early Warning and Intervention, where they enable privacy-preserving synthetic data generation for predictive learning analytics. SQL-based systems and natural-language query agents appear only in Analytics Interpretation and Sensemaking and Strategic Institutional Planning.

One notable structural gap in Table I is the absence of RAG-based systems within macro-level decision categories. Although RAG technologies are represented in several micro- and meso-level applications, none of the reviewed macro-level studies identified their use. This pattern suggests a potential area for future research, particularly given the growing importance of transparency, traceability, and evidence-informed decision-making in higher education institutions. Whether this absence reflects implementation challenges, research priorities, or the relative novelty of RAG technologies remains unclear from the current evidence base. The next section builds on these findings

by examining how educational data and GenAI capabilities support the identified educational decisions.

B. Data and GenAI Capabilities Enabling Educational Decisions (RQ2)

Table II summarises the educational data sources, stakeholders, and GenAI capabilities associated with each decision category across the 38 reviewed studies.

1) *Mechanisms at the micro-level:* Individual learner data form the foundation of all three micro-level decision categories. Across Feedback and Assessment Support, Learning Pathway

Personalisation, and Academic Guidance and Advising, studies draw on assessment responses, LMS interaction logs, reflection texts, discussion forum contributions, student engagement data, and navigation histories to identify learner characteristics, engagement patterns, and learning needs. Natural language generation (NLG), often combined with conversational support mechanisms, translates these insights into personalised feedback, recommendations, adaptive guidance, and other learner-facing outputs that support educational decision-making.

TABLE II. DECISION-LEVEL MAPPING: STAKEHOLDERS, DATA SOURCES, GENAI CAPABILITIES, AND STUDIES

Decision Level	Decision Category	Stakeholder(s)	Educational Data Source	GenAI Capability	Studies
Micro (Learner-Facing)	Feedback and Assessment Support	Students, Instructors	Student handwritten notes, writing assignments, open-ended responses, discussion forum posts, online activity data, LMS interaction logs, feedback trace logs	NLG for personalised and scalable feedback; RAG-grounded formative assessment generation; LLM rubric interpretation and tag-based recommendation; dialogue-based scaffolding of analytics feedback	[15], [16], [17], [18], [19], [20], [21], [22]
	Learning Pathway Personalisation	Students, Instructors	Multimodal data (speech, facial expression, text), discussion forum posts, student engagement and behavioural data, large-scale MOOC datasets, real-time navigation and activity logs	Adaptive scaffolding generation from real-time trace data; multimodal chain-of-thought pathway planning; RAG-guided learning objective alignment; NLP-based engagement analysis to support adaptive personalisation	[22], [23], [24], [25], [26]
	Academic Guidance and Advising	Students, Academic advisors	Student course enrolment data, advising survey responses, advisor evaluation records, focus group transcripts, AI-assisted learning interaction data	Profile-aware NLG course recommendation; LLM rule-based course matching; GPT-based major selection advising with advisor comparison; qualitative thematic analysis for student perspective understanding	[6], [27], [28], [29]
Meso (instructor/Program)	Instructional Design Support	Instructors, Curriculum designers	Multimodal classroom data (speech, facial expression, text), question bank datasets, student reflective writing, student interaction and behavioural trace logs, course data	Multimodal LLM analysis for iterative course redesign; LLM-based automated learning objective labeling; reflection analysis for instructor insights; ERNIE Bot-based human-AI collaboration analysis; LLM co-creation of instructional materials	[25], [30], [31], [32], [33]
	Collaborative Learning Analytics	Instructors, Researchers, Administrators	Discussion forum posts, asynchronous peer discussion datasets, mixed reality interaction logs, student reflection texts, video recordings of collaborative tasks, multimodal data (eye-tracking, interaction logs, dialogue)	LLM-based cognitive presence detection and summarisation; automated SSRL phase coding; process mining of knowledge construction sequences; grounded prompt engineering for deductive coding (GROPROE); multimodal LLM posture annotation; help-seeking process analysis	[23], [34], [35], [36], [37], [38]
	Analytics Interpretation and Sensemaking	Students, Instructors, Administrators	Online learning activity logs and peer review data, descriptive LA task datasets, LA dashboard interaction datasets, student reflection and GenAI assistant interaction logs	GPT-4o + RAG conversational agents for dashboard interpretation; NL-based dashboard and visualisation generation; ChatGPT code interpreter for descriptive analytics support; multimodal GenAI + RAG scaffolding for visual analytics comprehension; dialogue-based scaffolding of analytics feedback	[5], [18], [39], [40], [41]
Macro (Institutional)	Early Warning and Intervention	Instructors, Advisors, Academic support staff	Campus card transaction and exam score data, student engagement and behavioural data, lecture slides and assessment records, ChatGPT interaction logs, e-book interaction logs including reading time and page interactions	LLM + GNN graph embedding for multi-source behavioural analysis and risk detection; GPT-4 + NLP for engagement-driven predictive insights; LLM-driven ontology extraction and knowledge graph construction for performance prediction; ChatGPT-based feature extraction from conversation logs; LLM agent for e-book interaction factor analysis	[26], [42], [43], [44], [45]
	Strategic Institutional Planning	Administrators, Institutional researchers	Retention data, GPA trends and graduation rate records, campus card and exam score data, student survey responses, focus group transcripts, online learning datasets, descriptive LA task datasets, AI-assisted learning interaction data	Automated SQL query generation for institutional data access; LLM + GNN multi-source report generation; LLM-based sentiment analysis and summarisation of student surveys; GPT-4 + Claude qualitative thematic coding; GPT-4o NL dashboard generation and visualisation; ChatGPT code interpreter for non-expert analytics support; GPT-Turbo generative learning insights	[5], [27], [29], [40], [45], [48], [49]

Retrieval-Augmented Generation (RAG) strengthens several micro-level applications by grounding outputs in domain-specific educational content, including course rubrics, learning objectives, and disciplinary knowledge, thereby improving factual consistency and contextual relevance [22], [39]. Studies employing RAG generally emphasise grounding mechanisms as a means of improving the reliability and contextual relevance of generated outputs. A complementary quality-assurance pattern is also evident. Studies without RAG frequently incorporate instructor review between GenAI output generation and learner delivery (Xavier et al., 2025; Lekan & Pardos, 2025), whereas RAG-enabled systems are more often implemented with higher levels of automation. This pattern suggests that both RAG and human oversight may serve as complementary mechanisms for enhancing output quality and reliability at the micro level.

Despite relying on similar GenAI technologies, the micro-level decision categories differ in the learner data they use and the decisions they support. Feedback and Assessment Support focuses on assessment-related decisions through personalised feedback, formative assessment, rubric interpretation, and other feedback mechanisms that support learner improvement. In contrast, Learning Pathway Personalisation uses behavioural, engagement, and multimodal learner data to adapt future learning experiences, content sequencing, and instructional pathways to individual learner needs. Academic Guidance and Advising combines learner records, advising information, and student perspectives to support course selection, programme planning, and academic progression. These differences reflect distinct educational objectives and decision contexts despite their reliance on similar underlying GenAI capabilities. Treating them as a single analytical category would therefore obscure important differences in the learner data, decision processes, and evaluation approaches associated with each category.

2) *Mechanisms at the meso-level:* The analytical challenge at the meso level shifts from individual personalisation to cohort-level pattern detection. Collaborative Learning Analytics draws on one of the widest ranges of educational data in the corpus, including discussion forum posts, video recordings, group activity logs, student reflections, and multimodal interaction data. Across the reviewed studies, multimodal LLM annotation and process mining are used to extract meaningful pedagogical signals from these collaborative interactions [37], [38], [50]. A nuanced distinction exists between behavioural coding (classifying what interaction types occurred) and process mining (mapping temporal sequences and dynamics of collaboration): both are present in the evidence base, but few studies combine them. The limited integration of these two analytical modes suggests an opportunity for richer and more actionable collaborative decision support.[37], [38], [50]

Instructional Design Support uses aggregated cohort data to generate curriculum and instructional recommendations, typically through a pattern analysis stage that informs subsequent NLG [30], [31]. GenAI in this category identifies which learning objectives, topics, or instructional sequences are

associated with persistent underperformance, then generates specific redesign suggestions for instructors.

Analytics Interpretation and Sensemaking relies on a highly diverse capability set, combining natural-language querying, RAG-augmented explanation, and dialogue-based scaffolding to support stakeholders with varying levels of technical expertise, from non-technical administrators querying databases [40] to students interpreting their own performance patterns [18]. Unlike the other meso-level categories, the primary contribution of this category lies not in generating new analytical insights but in enabling stakeholders to understand and act upon existing learning analytics through conversational and context-aware interactions.

Together, the three meso-level categories illustrate complementary mechanisms through which GenAI supports instructor- and programme-level decision-making. Collaborative Learning Analytics focuses on extracting pedagogical insights from complex interaction data, Instructional Design Support translates cohort-level patterns into curriculum improvements, and Analytics Interpretation and Sensemaking makes analytical outputs more accessible to stakeholders through natural-language interaction and contextual explanation. These differences demonstrate that GenAI supports meso-level decisions not only by generating new insights but also by improving stakeholders' ability to interpret and act on existing learning analytics.

3) *Mechanisms at the macro-level:* At the macro level, educational decisions are informed by institution-wide educational data, including student information systems, retention records, survey responses, campus card transactions, and longitudinal behavioural data. These broader and more integrated data sources enable GenAI capabilities that support institution-wide risk identification, strategic planning, and organisational decision-making.

Early Warning and Intervention combines multiple educational data sources to identify students at risk of academic failure or disengagement. The reviewed studies employ complementary GenAI technologies, including graph neural networks (GNNs), large language models (LLMs), and GAN-based synthetic data generation. GNNs are used to model the relational and temporal structure of student behavioural data, while LLMs translate analytical outputs into natural-language risk summaries and intervention recommendations [26], [42], [45]. GAN-based approaches generate privacy-preserving synthetic educational data that support the development, evaluation, and validation of predictive learning analytics models when authentic educational data are limited [46], [47]. Together, these complementary capabilities strengthen institution-wide risk identification and intervention.

Strategic Institutional Planning draws on institutional datasets, including graduation records, retention data, survey responses, and administrative databases, to support strategic and operational decisions. Natural-language querying and SQL-based interfaces improve access to institutional analytics by enabling administrators to interrogate complex data through conversational interaction, thereby supporting evidence-informed planning and decision-making [5], [40], [49].

4) Cross-level patterns, contradictions, and research gaps:

Across the reviewed studies, three cross-level patterns emerge. First, learner-generated educational data, including LMS interaction logs, assessment records, and behavioural traces, form the primary foundation for GenAI-supported educational decisions across all three levels, although multimodal and institutional data become increasingly important at the meso and macro levels. This pattern reflects the growing maturity of educational data infrastructures supporting GenAI applications in higher education [2].

Second, human oversight varies across decision levels. At the micro level, studies report both augmentation approaches, where instructors review GenAI-generated outputs before learner delivery [6], [16], and automation approaches, where outputs are delivered with minimal human intervention [17], [20]. In contrast, macro-level applications consistently position institutional stakeholders as the primary decision-makers, with GenAI supporting rather than replacing institutional judgment [5], [40], [49].

Third, GenAI capability selection appears to depend on the educational task. Studies comparing proprietary GPT-family and open-source LLMs for learner-facing natural language generation generally report stronger performance for GPT-family models in the reviewed studies for feedback and advising tasks [6], [15]. In contrast, studies employing open-source LLMs for behavioural coding and analytical tasks report comparable performance while highlighting advantages in cost, privacy, and local deployment [34], [35], [36]. At the macro level, complementary techniques such as GNNs and GANs extend GenAI capabilities by supporting relational modelling and privacy-preserving synthetic data generation for predictive learning analytics [42], [46], [47].

Among the research gaps identified across the reviewed studies, limited evidence on the long-term effectiveness of GenAI-supported educational decisions and the relatively limited attention to responsible AI governance emerged as particularly important. Only one study [17] evaluated outcomes across multiple semesters, while fairness, transparency, and accountability were seldom addressed despite the increasing use of GenAI in educational decision-making. These cross-level patterns and research gaps informed the development of the GDEDM framework presented in the following section.

C. The GDEDM Framework (RQ3)

The findings from RQ1 and RQ2 reveal a consistent structural logic across the evidence: educational data provide the foundation for GenAI capabilities, which enable educational decisions operating within responsible AI governance. The GDEDM (Generative AI-Driven Educational Decision-Making) framework formalises this logic as four interconnected layers, illustrated in Fig. 2. Unlike frameworks that describe analytical workflows or system architectures, GDEDM is organised around the conceptual relationships between educational data, GenAI capabilities, educational decisions, and responsible AI governance, making it applicable as both a scholarly explanatory model and a practical reference for institutional GenAI adoption.

1) *Layer 1 – Educational data sources*: Layer 1 comprises the educational data that underpin all GenAI-supported educational decisions. The framework distinguishes two complementary data sources: learner-generated data, representing learning activities, assessment, and behavioural traces, and institutional data, comprising academic and administrative records that support institution-wide decision-making. The quality and representativeness of these data determine which educational decisions can be supported and how reliably they can be informed. Richer multimodal data, including classroom recordings, eye-tracking, and posture traces, expand decision support to collaborative and immersive learning contexts [37], [38], [50] while introducing additional privacy obligations and processing complexity. Consequently, data quality is fundamental to trustworthy decision-making [37], [38], [50].

2) *Layer 2 – GenAI capabilities*: Layer 2 comprises five complementary GenAI capabilities: Natural Language Generation, Behavioural and Semantic Analysis, Multimodal Processing, Conversational Analytics, and Synthetic Data Generation. Natural Language Generation produces personalised feedback, recommendations, and other educational outputs; Behavioural and Semantic Analysis extracts meaningful patterns and insights from learner interactions and educational data; Multimodal Processing integrates and interprets heterogeneous educational data, including text, speech, video, and behavioural traces; Conversational Analytics enables natural-language interaction with learning analytics and institutional data, supporting query generation, dashboard visualisation, and contextual interpretation; and Synthetic Data Generation creates privacy-preserving datasets for developing, evaluating, and validating AI-supported educational decision systems when authentic educational data are limited.

Retrieval-Augmented Generation (RAG) functions as a cross-cutting quality mechanism within Layer 2 by grounding LLM outputs in verified educational content, thereby improving factual consistency and trustworthiness [22], [39]. Among the reviewed studies, RAG was not applied in macro-level decision support, representing an opportunity to enhance the transparency and reliability of institutional GenAI applications.

3) *Layer 3 – Educational decisions*: Layer 3 organises the eight evidence-derived educational decision categories into three decision levels. The micro level comprises learner-facing decisions (Feedback and Assessment Support, Learning Pathway Personalisation, and Academic Guidance and Advising); the meso level supports instructor- and programme-level decisions (Instructional Design Support, Collaborative Learning Analytics, and Analytics Interpretation and Sensemaking); and the macro level supports institution-wide decisions (Early Warning and Intervention and Strategic Institutional Planning).

Together, these levels represent a progression from individual learner support to organisational decision-making, with increasing stakeholder responsibility and governance requirements. This progression provides a practical roadmap for

institutional GenAI adoption, enabling lower-risk learner-facing applications before extending deployment to institution-wide decision support requiring more comprehensive governance.

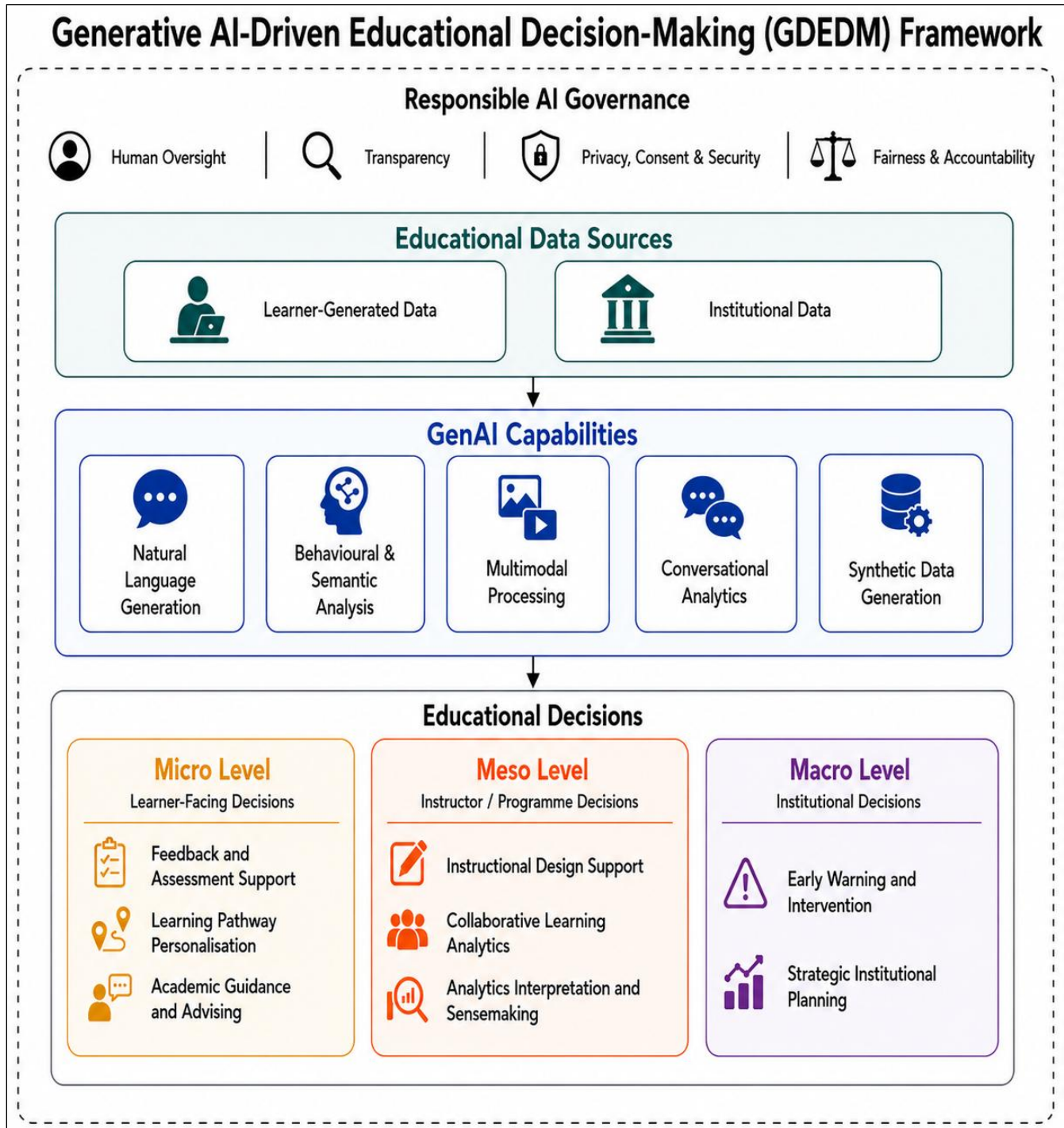


Fig. 2. The GDEDM framework.

4) *Layer 4 — Responsible AI governance*: Governance is represented as an overarching layer surrounding the framework, ensuring that responsible AI principles apply across educational data, GenAI capabilities, and educational decisions. The framework highlights four governance principles: Human

Oversight, Transparency, Privacy, Consent and Security, and Fairness and Accountability. Human Oversight ensures meaningful human authority over consequential educational decisions. Transparency supports explainable GenAI outputs. Privacy, Consent and Security govern the responsible

management of educational data, while Fairness and Accountability require institutions to monitor bias and maintain clear responsibility for GenAI-supported decisions. Together, these principles embed governance across all layers of the framework rather than treating it as a separate implementation stage.

The review also highlights several governance priorities for institutional GenAI adoption. None of the reviewed studies systematically evaluated whether GenAI-supported decisions produced differential outcomes across student demographic groups despite well-established concerns regarding algorithmic bias [3], [7]. Consequently, the GDEDM framework emphasises fairness and accountability through equity auditing, particularly for macro-level decisions affecting institutional planning, resource allocation, and student success. Responsible deployment also requires transparency, informed consent, data minimisation, human oversight, and clearly defined accountability. Together, these governance principles support trustworthy GenAI-enabled educational decision-making.

IV. DISCUSSION

The GDEDM framework and its evidential foundations offer three broader insights into the adoption of GenAI for educational decision-making in higher education.

First, organising the literature around educational decisions rather than GenAI technologies reveals research priorities that are less apparent in technology-centred reviews. The eight educational decision categories show that evidence is strongest for Feedback and Assessment Support ($n = 8$), whereas Academic Guidance and Advising ($n = 4$) and Instructional Design Support ($n = 5$) remain comparatively underexplored despite their importance for improving student success and teaching quality. These findings suggest that future research should extend beyond feedback generation to investigate how GenAI can support a broader range of educational decisions across learners, instructors, and institutions.

Second, the review identifies a governance gap between rapidly advancing GenAI capabilities and institutional safeguards. GenAI systems are increasingly being deployed to support decisions at the micro, meso, and macro levels, yet relatively few studies explicitly address governance mechanisms such as transparency, human oversight, privacy, or fairness. The GDEDM framework therefore positions responsible AI governance as a cross-cutting layer, demonstrating that governance should accompany educational data, GenAI capabilities, and educational decisions rather than being considered only after deployment.

Third, the review highlights explainability as a critical requirement for trustworthy educational decision-making. At the micro level, GenAI frequently delivers personalised feedback, recommendations, and guidance directly to learners. However, students and educators may be unable to judge whether these outputs are accurate, appropriate, or free from bias. Developing explainable GenAI systems that provide understandable justifications for educational recommendations therefore represents an important direction for future research and practical implementation.

These findings should, however, be considered in light of several limitations. The search was restricted to three databases and English-language publications, potentially introducing coverage and publication bias. In addition, the literature search was completed in March 2026; therefore, studies published thereafter were not included. Although grounded in 38 empirical studies, the GDEDM framework has not yet been independently validated through expert assessment or real-world institutional application.

V. CONCLUSION

This study presented a PRISMA-guided systematic review of 38 empirical studies examining how GenAI supports educational decision-making in higher education. For RQ1, eight educational decision categories were identified and organised into micro-, meso-, and macro-level decisions. Feedback and Assessment Support ($n = 8$), Early Warning and Intervention ($n = 7$), and Strategic Institutional Planning ($n = 7$) were the most frequently represented categories, whereas Academic Guidance and Advising ($n = 4$) remained comparatively underexplored.

For RQ2, five GenAI capability categories were identified, demonstrating how natural language generation, behavioural and semantic analysis, multimodal processing, conversational analytics, and synthetic data generation enable different forms of educational decision-making across stakeholders and institutional contexts. For RQ3, this study proposed the GenAI-Driven Educational Decision-Making (GDEDM) framework, a four-layer model connecting educational data sources, GenAI capabilities, educational decisions, and responsible AI governance. The framework provides both a conceptual explanation of GenAI-supported educational decision-making and a basis for future research and evaluation of responsible institutional adoption.

The review identifies three priorities for future research. First, longitudinal and multi-institutional studies are needed to evaluate the long-term effectiveness of GenAI-supported educational decisions. Second, systematic evaluation of fairness and accountability, including equity auditing, is required to support trustworthy institutional deployment. Third, explainable GenAI approaches should be developed to improve transparency and stakeholder trust across learner-, instructor-, and institution-facing applications. Overall, the GDEDM framework provides an evidence-based model that integrates educational data, GenAI capabilities, educational decisions, and responsible AI governance to support responsible GenAI adoption in higher education, thereby contributing to the advancement of inclusive and high-quality higher education in support of Sustainable Development Goal 4 (SDG 4: Quality Education).

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