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Review Article

Beyond Dashboards: A Systematic Literature Review of Learning Analytics, Business Intelligence, and Generative AI for Decision-Making in Universities

Heri Purwanto [1,2,*], R. Rizal Isnanto [1], Qidir Maulana Binu Soesanto [1], Agus Nursikuwagus [3], and Fahmi Reza Ferdiansyah [4]

[1] Doctoral Program of Information Systems, School of Postgraduate Studies, Diponegoro University, Semarang 50241, Indonesia;
e-mail : hpurwanto@students.undip.ac.id; rizal@ce.undip.ac.id; qidirbinu@fisika.fsm.undip.ac.id
[2] Information System Department, Universitas Sangga Buana, Bandung 40124, Indonesia;
e-mail : heri.purwanto@usbypkp.ac.id
[3] Informatics Management Department, Universitas Komputer Indonesia, Bandung 40132, Indonesia;
e-mail : agusnursikuwagus@email.unikom.ac.id
[4] Information System Department, Universitas Ekuitas, Bandung 40124, Indonesia;
e-mail : fahmi.reza@ekuitas.ac.id
* Corresponding Author : Heri Purwanto

Abstract: The rapid proliferation of learning analytics, business intelligence (BI), artificial intelligence (AI), and generative AI (GenAI) has significantly expanded universities' ability to collect, integrate, analyze, and operationalize institutional data. However, despite advances in predictive analytics, dashboards, and AI-driven systems, the translation of analytical outputs into consistent and accountable institutional decision-making remains uneven. This systematic literature review synthesizes contemporary research on analytics-enabled decision-making in higher education with the aim of moving beyond dashboard-centric perspectives toward a socio-technical and computing-oriented understanding of how data are transformed into institutional actions and outcomes. Guided by the PRISMA framework, the review synthesizes evidence across four interconnected dimensions: data ecosystems and learning analytics foundations; analytics capability, BI adoption, and digital readiness; AI and advanced analytics for decision support; and human-in-the-loop (HITL) decision routines and institutional outcomes. The findings show that predictive performance and analytical sophistication alone do not guarantee decision value. Instead, effective analytics-enabled decision-making depends on interoperable data ecosystems, organizational analytics capability, governance mechanisms, explainability, and sustained human oversight. Based on these findings, this review contributes a computing-oriented decision-intelligence framework that conceptualizes analytics-enabled decision-making as an end-to-end socio-technical pipeline linking heterogeneous data acquisition, integration, feature construction, analytical modeling, explainability, human validation, governance, and feedback-based refinement. By integrating learning analytics, BI, AI, GenAI, and HITL mechanisms within a unified framework, the review clarifies how universities can move beyond dashboard-based reporting toward accountable, adaptive, and institutionally actionable decision-support infrastructures.

Keywords: Artificial intelligence; Business intelligence; Data-driven decision-making; Decision intelligence; Generative artificial intelligence; Higher education; Human-in-the-loop; Learning analytics.

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1. Introduction

Learning analytics (LA) and business intelligence (BI) in higher education have evolved substantially over the past decade, shifting from static dashboard-based reporting toward decision-oriented intelligence that increasingly shapes institutional actions and outcomes. Early implementations of analytics in universities primarily emphasized descriptive visualization of key performance indicators, providing visibility into student performance, engagement, and operational metrics. More recently, advances in predictive analytics and artificial intelligence (AI) have enabled universities to move beyond monitoring toward proactive and data-driven decision-making. Machine learning applications for predicting academic performance, for example, are increasingly used to support curriculum redesign, intervention strategies, and resource allocation, illustrating how analytics capabilities are becoming embedded within institutional decision processes rather than functioning merely as reporting layers [1].

Despite these technological advances, the literature consistently shows that improved visibility does not automatically translate into improved decisions. The availability of analytics dashboards and predictive outputs frequently fails to produce meaningful institutional action, particularly when ethical considerations, interpretive challenges, governance mechanisms, and organizational constraints remain insufficiently addressed. Study [2] note that issues surrounding data transparency, interpretation, and ethical use remain underdeveloped in educational analytics, limiting the actionability of analytical insights. Similarly, large-scale analyses of LA adoption across European higher education institutions reveal persistent gaps between technical capability and institutional implementation, with many universities struggling to operationalize analytics in ways that meaningfully influence pedagogical and strategic decision-making.

Within contemporary universities, LA, BI, and AI collectively support decision-making across instructional, managerial, and operational domains by transforming heterogeneous institutional data into actionable insights. LA enables institutions to examine student behaviors, engagement patterns, and learning outcomes to support instructional strategies and student interventions [1]. BI complements this role by aggregating and structuring analytical outputs to inform managerial decisions related to planning, budgeting, and resource allocation, thereby enhancing organizational effectiveness and strategic alignment [2]. AI further extends analytics-enabled decision-making through predictive, adaptive, and automated capabilities that support risk anticipation, personalized learning pathways, and administrative optimization [3], [4].

More recently, generative AI (GenAI) has emerged as a transformative layer within institutional analytics ecosystems, enabling real-time synthesis, feedback generation, and scenario exploration based on complex data inputs. Empirical studies demonstrate that integrating GenAI with LA can support instructional decision-making through faster pedagogical adaptation and richer feedback mechanisms [5]. At the same time, concerns regarding bias, equity, transparency, and responsible use remain prominent, underscoring the need to align AI-enabled insights with human judgment and institutional values [1], [6].

Although analytics technologies are becoming increasingly sophisticated, several socio-technical challenges continue to constrain their institutional impact. Data quality remains a foundational concern, as incomplete, inconsistent, or poorly governed datasets can undermine the reliability of analytics outputs and lead to misguided decisions [1]. Interoperability across institutional systems—including learning management systems, student information systems, and administrative platforms—poses another major challenge because the absence of shared standards and integration mechanisms restricts holistic analysis and cross-functional decision-making [7]. Organizational and cultural factors further influence analytics adoption, including resistance among faculty and staff, limited data literacy, and misalignment between analytics initiatives and pedagogical practices [8]. In parallel, governance structures in many universities remain insufficiently prepared to oversee ethical, transparent, and accountable analytics use, raising concerns related to privacy, accountability, and access control [9].

Collectively, these challenges contribute to what the literature describes as the "insight–action gap," namely the persistent disconnect between generating analytical insights and translating them into concrete institutional actions. Empirical evidence suggests that universities often collect extensive data and generate sophisticated analytical outputs without achieving corresponding changes in institutional practice or policy [10]. This gap is frequently attributed to limited capacity among decision-makers to interpret analytics outputs, as well as weak integration of analytics into organizational workflows and decision routines [11]. Addressing the insight–action gap therefore requires more than technical solutions alone. Prior research emphasizes the importance of data literacy, cross-functional collaboration, stakeholder engagement, co-design, and organizational cultures that support evidence-informed decision-making [3], [12]. Building on this premise, the present review examines how learning analytics, BI, AI, and GenAI operate as interconnected components of institutional decision infrastructures and identifies the conditions under which analytics-enabled insights become actionable, trustworthy, and institutionally legitimate.

Prior reviews provide important but fragmented perspectives on analytics-enabled decision-making in higher education. Existing review streams commonly examine LA, BI, AI, and GenAI as separate domains rather than as interconnected components of integrated decision-support infrastructures. LA reviews primarily emphasize dashboards, engagement indicators, and risk prediction; BI-related studies focus on organizational readiness and reporting infrastructures; whereas AI and GenAI reviews foreground algorithmic capability, automation, ethics, and governance concerns [6], [13]–[15]. This fragmentation limits understanding of how data ecosystems, BI infrastructures, AI models, GenAI interfaces, governance mechanisms, and human decision routines collectively shape institutional decision-making processes.

A related limitation concerns the insufficient synthesis of end-to-end computational architectures and methodological trade-offs in higher education analytics research. Although prior studies discuss dashboards, predictive models, and AI-enabled tools, most reviews do not comprehensively synthesize how institutional data are acquired, integrated, preprocessed, modeled, validated, interpreted, and translated into institutional decisions [13], [15]. System-level discussions of governance, validation, monitoring, and model lifecycle management remain more developed in clinical and healthcare AI governance literature than in higher education analytics research [16]–[18]. Consequently, the higher education literature still lacks an integrated account of how computational pipelines, validation practices, explainability mechanisms, and methodological trade-offs shape the practical decision value of analytics systems.

Prior studies also document a persistent disconnect between analytics outputs and institutional action. Dashboards, predictive outputs, and risk scores frequently fail to trigger meaningful interventions when stakeholder engagement, governance mechanisms, workflow integration, and human oversight remain weak [13], [15], [19], [20]. Existing reviews increasingly call for stronger explainability, governance, continuous monitoring, and human-in-the-loop (HITL) mechanisms, yet implementation remains uneven compared with more mature governance practices in clinical AI settings [13], [17], [18]. These limitations suggest that the central challenge is not merely the availability of analytics technologies, but the absence of an integrated decision-intelligence perspective that connects data ecosystems, computational models, governance structures, human judgment, and institutional action.

The research gap addressed in this review is therefore threefold and grounded in limitations identified across prior review streams. First, existing reviews frequently examine LA, BI, AI, and GenAI separately, resulting in fragmented understanding of how these technologies jointly support institutional decision-making. Prior reviews in LA and AI in education emphasize dashboards, engagement metrics, predictive modeling, educational effectiveness, and AI applications, whereas BI and big-data analytics studies focus more heavily on readiness and reporting infrastructures than on integrated decision systems [1], [6], [13]–[15], [21]. Second, prior reviews largely emphasize adoption, effectiveness, or application domains while providing limited synthesis of end-to-end computational architectures, validation practices, methodological trade-offs, and model-level design considerations. This limitation becomes more apparent when compared with governance-oriented studies that explicitly address data integration, monitoring, provenance, and model lifecycle management [13], [15]–[18], [22], [23]. Third, the operational linkage between analytics outputs and institutional decisions remains underdeveloped, particularly with respect to explainability, governance, human validation, workflow integration, and feedback-based refinement. Evidence regarding the insight–action gap, limited uptake, and weak stakeholder integration suggests that dashboards and predictive outputs do not automatically translate into institutional action without governance mechanisms and HITL processes [13], [15], [17]–[20]. Addressing these evidence-based gaps is essential for understanding how universities can move beyond dashboard-oriented reporting toward accountable, adaptive, and decision-oriented analytics ecosystems.

To clarify the analytical boundaries of this review, the study examines analytics-enabled decision-making across three interconnected levels. First, at the computational-system level, the review considers how heterogeneous institutional data sources are acquired, integrated, processed, and transformed into analytical outputs. Second, at the methodological-model level, it examines algorithmic paradigms, model characteristics, validation approaches, and methodological trade-offs associated with LA, BI, AI, and GenAI applications. Third, at the socio-technical decision level, the review analyzes how analytical outputs are interpreted, governed, and translated into institutional action through HITL decision routines. Studies discussing educational technology adoption without analytics-enabled decision support, or organizational decision-making without computational and data-driven components, fall outside the scope of this review.

Unlike prior reviews that focus primarily on LA adoption, AI applications in higher education, or BI implementation as separate research streams, this review integrates these domains through a computing-oriented decision-intelligence perspective. Its novelty lies not only in synthesizing what analytics technologies are used in universities, but also in explaining how computational architectures, methodological trade-offs, governance mechanisms, and HITL configurations collectively shape decision quality. Accordingly, this review advances an operational framework that can be used to evaluate whether university analytics systems function merely as dashboard-oriented reporting tools or as accountable decision-support infrastructures.

2. Review Scope, Key Constructs, and Theoretical Lens

2.1. Review Positioning and Scope

To clarify the positioning of this review within the broader higher education analytics literature, Table 1 compares the present study with representative review streams on AI-supported tutoring, advanced educational technologies, LA, BI adoption, and AI in higher education. Prior reviews have generated important insights into learner-facing systems, educational technology effectiveness, organizational adoption, and AI-enabled educational applications. However, these streams are often examined independently and less frequently synthesized into an integrated decision-support perspective that connects data pipelines, computational models, governance mechanisms, validation processes, and HITL decision routines.

Table 1. Positioning of the present review against prior review studies.

Review Focus	Representative References	Typical Emphasis in Prior Reviews	Limitation from a Decision-Intelligence Perspective
AI-supported tutoring and feedback systems	[1], [13], [21], [24]	Personalized feedback, adaptive instruction, intelligent tutoring systems, learner modeling, dashboard usability, and learning outcomes	Primarily focuses on learner-level instructional interaction and pedagogy, with limited attention to institutional decision infrastructures
Advanced educational technologies	[8], [15], [22], [25]	Educational technology innovation, platform adoption, adaptive systems, big-data integration, and technology effectiveness	Emphasizes adoption and effectiveness, with comparatively limited attention to operational decision processes, governance, and end-to-end analytical pipelines
Learning analytics reviews	[1], [13], [21]	Student engagement, dashboard design, academic performance prediction, early-warning systems, and intervention support	Commonly centers on learner-level analytics and predictive performance, with limited synthesis of deployment architectures and institutional decision infrastructures
BI adoption reviews	[2], [8], [15], [26]	Organizational readiness, dashboard adoption, analytics capability, culture, infrastructure, and performance reporting	Frequently treats BI/BDA as organizational reporting or managerial capability rather than as an integrated computational decision stack
AI in higher education reviews	[1], [13], [21], [22], [27]	AI applications, predictive modeling, automation, intelligent systems, educational effectiveness, and ethical concerns	Primarily catalogues applications and ethical issues, with limited integration of BI architectures, governance mechanisms, validation practices, and complete decision pipelines

As summarized in Table 1, prior review streams have contributed substantially to understanding analytics, AI, and educational technologies in higher education. Nevertheless, these studies remain largely organized around separate emphases, including learner-facing interaction, technology adoption, dashboard utilization, organizational readiness, or AI applications. This separation limits understanding of how data ecosystems, BI infrastructures, AI models, governance mechanisms, GenAI interfaces, and HITL routines collectively function as institutional decision-support infrastructures. The present review addresses this gap by integrating LA, BI, AI, GenAI, governance, and HITL mechanisms through a computing-oriented decision-intelligence perspective.

2.2 Key Constructs and Operational Definitions

Because this review integrates concepts from education, information systems, data science, and AI governance, Table 2 defines the principal constructs used throughout the manuscript and grounds them in representative literature. The table clarifies both the operational meaning of each construct and the computing-oriented analytical boundary adopted in this review.

Table 2. Key constructs and operational definitions used in this review.

Construct	Key References	Operational Definition in This Review	Computing-Oriented Boundary
Learning analytics	[1], [13], [21], [28]	Collection, measurement, analysis, and reporting of learner-related data and learning contexts to support learning optimization, academic performance, and student-success decisions	Focuses on LMS/VLE traces, engagement indicators, academic risk signals, dashboard outputs, early-warning models, learning behavior data, and intervention support
Business intelligence	[2], [8], [15], [22], [23]	Institutional decision-support capability for integrating, structuring, analyzing, and visualizing organizational data to support managerial monitoring and strategic decision-making	Focuses on dashboards, data warehouses, ETL/ELT processes, metadata practices, KPI systems, reporting pipelines, and institutional performance monitoring
Analytics capability	[2], [15], [29]	Institutional capacity to transform data into reliable, interpretable, and actionable insights through aligned infrastructure, governance, skills, leadership, and decision routines	Includes data infrastructure, data quality, governance mechanisms, analytical expertise, model lifecycle management, and deployment readiness
Digital readiness	[19], [27], [30], [31]	Preparedness of institutions, users, and organizational systems to adopt and operationalize analytics, AI, and GenAI technologies within educational and administrative contexts	Includes technical infrastructure, user competence, digital literacy, leadership support, organizational routines, resource availability, and policy alignment
Decision intelligence	[32]–[35]	Integrative computational and socio-technical discipline connecting data, analytics, AI, human judgment, and organizational objectives to support accountable and actionable decisions	Focuses on data pipelines, analytical models, explainability, decision interfaces, workflow integration, monitoring, human validation, and feedback loops
Human-in-the-loop	[9], [19], [20], [34], [35]	Decision-control mechanism in which human expertise participates in model development, interpretation, validation, oversight, or contextual review of analytical outputs	Focuses on expert review, contextual interpretation, accountability, fairness assessment, governance oversight, workflow integration, and decision legitimacy
Generative AI	[5], [9], [36], [37]	AI systems, including large language models, capable of generating human-like outputs such as explanations, recommendations, summaries, feedback, and scenario-based responses	Limited to decision-support augmentation, explanation support, recommendation generation, scenario exploration, and interpretive assistance under human validation and governance

As shown in Table 2, the constructs adopted in this review span both educational and computational perspectives. LA and BI establish the analytical and reporting foundations for institutional visibility; analytics capability and digital readiness determine whether institutions can operationalize these systems effectively; decision intelligence connects data pipelines, computational models, and organizational decision processes; while HITL and GenAI clarify how human judgment and generative systems interact within accountable decision-support environments. Together, these definitions establish the conceptual boundaries that guide the theoretical discussion in the following section.

2.3. Theoretical Foundations for Analytics-Enabled Decision-Making

2.3.1. Technology Adoption Perspectives

The adoption and institutionalization of LA, BI, and AI in higher education have been widely examined through established technology-adoption and organizational-capability theories. Among these, the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) provide foundational explanations for how individuals and institutions adopt analytics-enabled systems. TAM emphasizes perceived usefulness and perceived ease of use as primary determinants of technology adoption, suggesting that faculty members and administrators are more likely to adopt analytics, BI, and AI systems when these technologies demonstrably enhance educational quality and administrative efficiency [38]. In higher education contexts, these perceptions influence whether analytics systems become integrated into routine teaching, learning, and management practices or remain peripheral and experimental.

The UTAUT extends TAM by incorporating additional constructs—performance expectancy, effort expectancy, social influence, and facilitating conditions—that collectively explain technology adoption within organizational settings [15]. In universities, performance expectancy reflects beliefs regarding how analytics and AI improve teaching effectiveness and institutional outcomes, whereas effort expectancy relates to usability and cognitive burden. Social influence captures the role of peers, leadership, and institutional norms in legitimizing analytics adoption, while facilitating conditions refer to the availability of infrastructure, training, and organizational support required for sustained implementation [16]. Empirical studies consistently show that these factors interact, with perceived usefulness often emerging as the strongest driver of adoption, reinforced by institutional readiness and social endorsement [17]–[19].

Figure 1 illustrates how analytics-enabled decision-making in higher education is grounded not in a single explanatory theory, but in the interaction of complementary socio-technical perspectives. Building on the discussion in this section, the figure integrates technology-adoption theories, analytics capability and maturity models, and governance-oriented perspectives into a unified conceptual framework. Integrated theoretical perspectives underlying analytics-enabled decision-making in higher education, including technology adoption theories (TAM and UTAUT), analytics capability and maturity frameworks, governance mechanisms, and HITL decision processes.

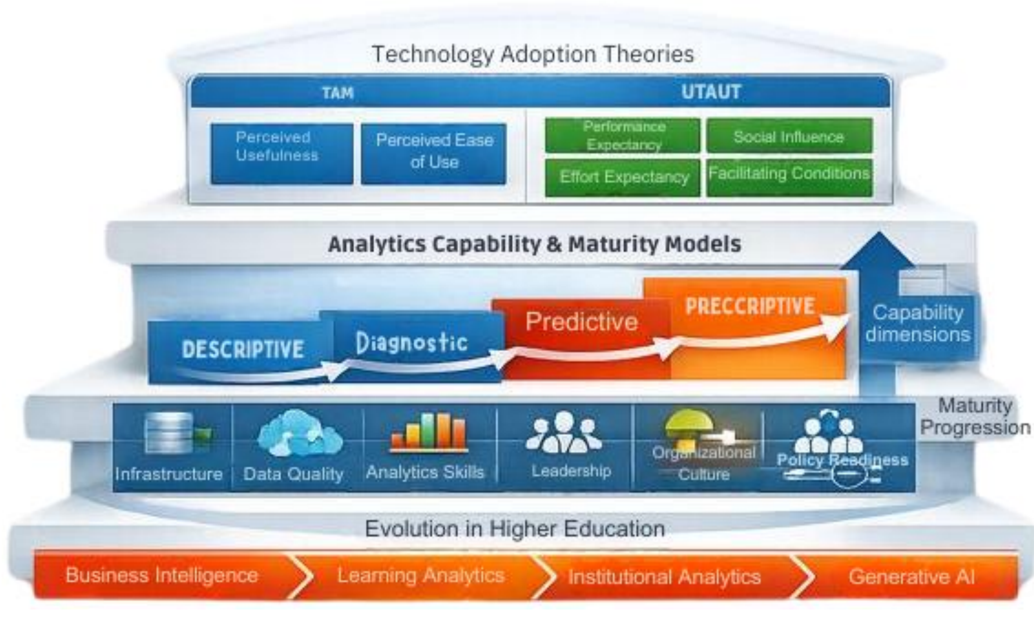

Figure 1. Theoretical Foundations of Analytics-Enabled Decision-Making in Higher Education.

As illustrated in Figure 1, adoption theories such as TAM and UTAUT explain why individuals and institutions choose to implement LA, BI, and AI systems through constructs such as perceived usefulness, performance expectancy, and facilitating conditions. However, adoption alone does not guarantee decision impact. The transition from descriptive and diagnostic analytics toward predictive and prescriptive decision-making depends on broader organizational capabilities, including infrastructure quality, data governance, leadership support, analytical expertise, and institutional readiness.

The broader evolution of analytics in higher education further contextualizes these developments, reflecting the progression from traditional BI systems toward LA, institutional analytics, and more recently GenAI-enabled decision support. This transition has accelerated following the COVID-19 pandemic and the rapid expansion of AI-driven educational technologies. Across these stages, persistent tensions involving data quality, interoperability, governance, ethics, and the balance between algorithmic outputs and human judgment continue to shape analytics-enabled decision-making.

While TAM and UTAUT explain why institutions adopt analytics technologies, they provide limited explanation of how such technologies function operationally as computational decision-support systems. Accordingly, this review extends adoption-oriented perspectives by conceptualizing analytics-enabled decision-making as an end-to-end computational pipeline involving data acquisition, integration, preprocessing, analytical modeling, validation, interpretation, deployment, and feedback monitoring. This extension is important because institutional adoption alone does not guarantee decision value unless the underlying analytical pipeline is technically reliable, interpretable, and governable.

2.3.2. Analytics Capability and Organizational Maturity

Beyond technology adoption, the literature increasingly conceptualizes analytics as an organizational capability that develops progressively through stages of institutional maturity. Analytics capability and maturity models, often influenced by the Capability Maturity Model (CMM), describe how institutions evolve from ad hoc and descriptive data use toward predictive and prescriptive analytics embedded within organizational decision routines [39].

These models typically evaluate multiple dimensions, including governance structures, technological infrastructure, analytical expertise, leadership commitment, and organizational culture, to assess how effectively institutions leverage data for decision-making. Measurement approaches frequently combine quantitative indicators, such as Likert-scale readiness assessments, with qualitative evaluations of leadership support, institutional coordination, and stakeholder engagement [40], [41].

In this review, analytics capability is operationalized as an evaluative framework rather than a purely descriptive construct. Analytics-enabled decision systems are examined across seven interconnected operational layers: data sources, integration mechanisms, analytics and modeling, explainability, governance, decision-action processes, and feedback-learning mechanisms. These layers enable evaluation of whether a system merely reports information, predicts outcomes without institutional uptake, or supports accountable and adaptive decision-making.

The maturity of analytics capability has been shown to significantly influence decision quality in higher education institutions. Universities with higher levels of analytics maturity are better positioned to integrate analytical insights into strategic planning and operational processes, thereby enabling more responsive and evidence-informed decisions [40]. Empirical evidence further indicates that mature analytics environments are associated with improved student satisfaction, stronger retention outcomes, and more effective allocation of institutional resources because analytical outputs are systematically linked to interventions and policy decisions [42], [43]. In addition, analytics maturity contributes to the development of data-informed institutional cultures in which administrators and faculty increasingly rely on empirical evidence rather than intuition alone [41], [44], [45].

2.3.3 Governance, Explainability, and Human-in-the-Loop Decision-Making

Governance, data quality, and interoperability further shape the legitimacy and trustworthiness of analytics-enabled decision-making. Governance frameworks define the policies, accountability structures, and institutional controls that ensure data are collected, managed, and used ethically and transparently. Without robust governance, analytics systems risk reinforcing bias, violating privacy, or producing decisions that lack institutional legitimacy [46], [47].

Data quality—including accuracy, consistency, completeness, and reliability—remains equally critical because poor-quality data undermine the validity of analytical outputs and reduce trust in decision processes [45], [48]. Interoperability among institutional systems enables integration of heterogeneous data sources across learning management systems, student information systems, and administrative platforms, thereby supporting holistic analysis and coordinated decision cycles spanning instructional, managerial, and operational domains [49], [50].

At the same time, the increasing use of algorithmic decision-making introduces tensions between automated outputs and human judgment. Algorithms may amplify biases embedded in training data and obscure decision rationales, raising concerns regarding fairness, accountability, and explainability in high-stakes educational contexts [51], [52]. These concerns have led to growing interest in HITL frameworks, which advocate maintaining human oversight throughout critical stages of analytical decision processes.

HITL approaches position analytics and AI systems as decision-support mechanisms rather than autonomous decision-makers, allowing human expertise to contextualize, validate, and when necessary override algorithmic recommendations [52], [53]. By integrating human judgment with computational efficiency, HITL frameworks help reconcile ethical accountability with analytical scalability, thereby strengthening the legitimacy and trustworthiness of analytics-enabled institutional decisions [54], [55].

Collectively, these perspectives—spanning technology adoption, analytics capability, governance, explainability, and human-centered decision-making—provide the socio-technical foundation for understanding how LA, BI, AI, and GenAI shape institutional decision-making in higher education. More importantly, they demonstrate that effective analytics-enabled decision-making depends not on any single theoretical model, but on the interaction between technological capabilities, governance structures, organizational readiness, and human agency.

3. Review Methodology

This study adopts a systematic literature review (SLR) approach to synthesize and critically examine research on LA, BI, AI, and GenAI for decision-making in higher education. To ensure methodological rigor, transparency, and reproducibility, the review process was guided by the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework, which provides structured procedures for identifying, screening, assessing, and reporting relevant studies [34].

In addition to conventional SLR principles, the review incorporates selected scoping-review elements to accommodate the interdisciplinary and rapidly evolving nature of analytics and AI research in higher education. This scoping-oriented perspective enables broader mapping of conceptual, empirical, and methodological developments without imposing overly restrictive inclusion thresholds that could exclude emerging GenAI-related studies [35]. Where relevant, insights from umbrella reviews were also considered to contextualize findings within existing bodies of synthesized evidence and to identify convergence and divergence across prior review streams [36], [37].

The methodological orientation of this review was designed to support critical synthesis rather than descriptive cataloguing. Consequently, studies were not included solely because they mentioned AI, BI, or LA in higher education contexts. Instead, included studies were required to demonstrate explicit relevance to analytics-enabled decision-making by addressing at least one of the following dimensions: computational architecture, data integration, analytical or algorithmic methods, decision-support processes, governance mechanisms, explainability, or HITL decision routines.

Figure 2 presents the PRISMA flow diagram summarizing the identification, screening, eligibility assessment, and final inclusion of studies reviewed in this paper. Overview of the systematic review process following PRISMA guidelines, including database identification, duplicate removal, screening, eligibility assessment, and final study inclusion.

3.1. Literature Search Strategy and Data Sources

A comprehensive literature search was conducted across multiple academic databases to capture high-quality peer-reviewed studies relevant to analytics-enabled decision-making in higher education. Scopus and Web of Science were selected as the primary databases because of their broad interdisciplinary coverage, indexing reliability, and relevance to research at the intersection of education, information systems, data science, and artificial intelligence [56], [57]. To improve disciplinary coverage, supplementary searches were also conducted in ERIC and PubMed, particularly to capture studies linking LA with educational practice, institutional decision-making, and applied higher education contexts. Search queries were constructed using combinations of domain-specific keywords, including “learning analytics,” “business intelligence in education,” “data-driven decision-making,” “artificial intelligence,” and “higher education,” combined using Boolean operators (AND, OR) to refine and expand search results [58], [59].

The search process was iterative, with preliminary screening results used to refine keyword combinations, scope boundaries, and inclusion parameters in order to improve relevance and reduce retrieval noise. This iterative refinement process aligns with recommended practices for systematic searches in interdisciplinary and emerging research domains [41].

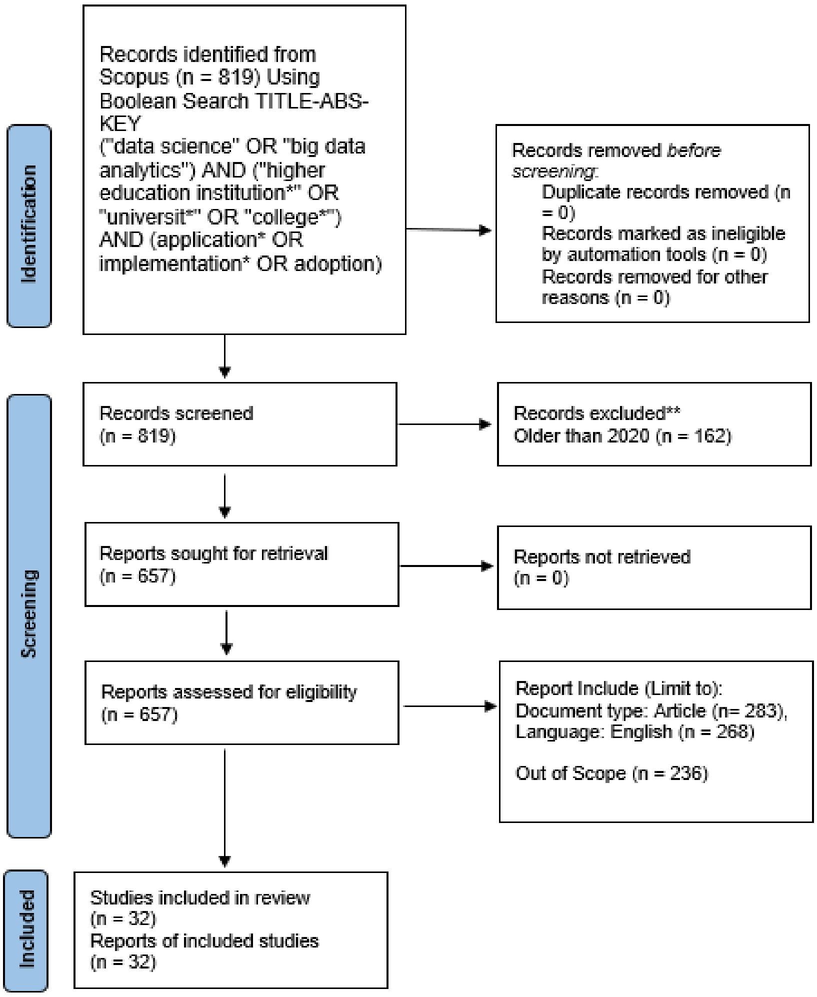

Figure 2. PRISMA Flow Diagram of Study Identification, Screening, Eligibility, and Inclusion.

3.2. Inclusion and Exclusion Criteria

Explicit inclusion and exclusion criteria were established to ensure methodological quality and substantive relevance to the objectives of this review. Included studies were required to be published in peer-reviewed journals, conference proceedings, or recognized review outlets to maintain academic rigor and credibility [60]. The temporal scope primarily focused on studies published within the last decade in order to capture recent developments in LA, BI, AI, and GenAI applications in higher education [61].

To ensure analytical relevance, studies were also required to explicitly address analytics-enabled decision-making in university contexts, including LA, BI, AI, or GenAI applications connected to institutional, instructional, managerial, or operational decision processes [62]. Methodological quality constituted an additional inclusion condition, with preference given to studies employing robust quantitative, qualitative, or mixed-method approaches capable of supporting meaningful analytical or empirical conclusions [60], [63].

Exclusion criteria included non-peer-reviewed sources, opinion articles, editorials, and grey literature lacking methodological transparency or empirical grounding [60]. Studies focusing exclusively on non-higher-education settings or lacking a clear relationship between analytics technologies and decision-support processes were also excluded [64]. To avoid redundancy and overrepresentation of similar evidence, duplicate and substantially overlapping studies were systematically screened and removed during the selection process [65].

3.3. Data Extraction, Coding, and Synthesis Approach

Data extraction focused on capturing information directly relevant to analytics-enabled decision-making in higher education, including study context, decision domain, analytics or AI methods, data sources, governance considerations, and reported institutional outcomes. Rather than relying solely on descriptive aggregation, the extracted data were synthesized thematically to enable cross-study comparison across instructional, managerial, operational, and strategic decision contexts. This synthesis-oriented approach supports the identification of recurring patterns, enabling conditions, methodological trade-offs, and persistent gaps in the literature, thereby aligning the review process with the broader objective of moving beyond dashboard-oriented reporting toward decision-centric and socio-technical analytics systems in higher education.

The synthesis process followed a structured coding framework. Each included study was coded according to four analytical dimensions:

- Computational layer, including data sources, integration mechanisms, analytical or AI model types, and explainability approaches;
- Methodological design, including validation strategies, evaluation metrics, robustness considerations, and reported limitations;
- Decision domain, including instructional, managerial, operational, and strategic decision contexts; and
- Governance and human-in-the-loop (HITL) mechanisms, including privacy, fairness, accountability, interpretability, oversight, and human validation practices.

This coding strategy enabled systematic identification of converging and diverging findings, methodological limitations, cross-study patterns, and unresolved research gaps across the reviewed literature.

4. Thematic and Computational Synthesis

4.1. Data Ecosystems and Learning Analytics Foundations for Decision-Making

This subsection synthesizes evidence on university data ecosystems, interoperability, and LA infrastructures, followed by a discussion of their broader computational, organizational, and governance implications for analytics-enabled decision-making.

4.1.1. Evidence Base and Key Patterns

The reviewed studies consistently indicate that richer and more heterogeneous institutional data ecosystems expand the potential value of analytics-enabled decision-making while simultaneously increasing computational, interoperability, and governance complexity. Across higher education contexts, universities increasingly integrate learning management systems (LMS), virtual learning environments (VLE), student information systems (SIS), assessment platforms, and multimodal learning data to support instructional, managerial, and operational decisions. However, the effectiveness of these analytical ecosystems depends heavily on interoperability, metadata consistency, data quality, and institutional governance mechanisms. Consequently, the primary challenge is no longer whether universities possess sufficient institutional data, but whether those data ecosystems are sufficiently integrated, interoperable, and governable to support reliable and actionable decisions. The empirical and review evidence synthesized in Table 3 highlights how institutional data ecosystems, interoperability mechanisms, and data quality collectively shape analytics-enabled decision-making in higher education.

Evidence across the reviewed studies shows how institutional data ecosystems and learning-analytics infrastructures can both enable and constrain analytics-enabled decision-making in higher education. Across these studies, a recurring finding is that analytics effectiveness depends less on isolated analytical tools than on the integration of heterogeneous data sources into coherent institutional ecosystems. Large-scale evidence from European higher education shows that although LA initiatives are increasingly widespread, their institutional impact remains uneven because of differences in organizational readiness, governance maturity, and data availability [13]. These findings help explain why many universities remain at descriptive or diagnostic stages despite growing investments in analytics infrastructures.

Empirical studies further demonstrate the value of integrating diverse data modalities. [70] show that combining structured learner background data with unstructured learning artifacts enables more nuanced identification of engagement patterns and help-seeking behaviors, thereby supporting instructional decision-making beyond what single-source LMS logs can provide. Similarly, [21], drawing on more than 5,500 student enrolments across 23 subjects over a five-year period, demonstrate that systematically organized LMS data can function as institutional analytical assets for monitoring engagement and informing pedagogical intervention. Their findings suggest that analytics value emerges when institutional data are structured across courses, organizational roles, and decision processes rather than analyzed in isolation.

Table 3. Evidence on university data ecosystems and learning-analytics foundations supporting analytics-enabled decision-making.

Refs.	Higher-Education Context and Decision Focus	Methodology and Data Sources	Data Ecosystem / Interoperability Focus	Key Findings Relevant to Analytics-Enabled Decision-Making
[48]	European higher education; institutional learning analytics adoption and decision-making	Consultations with senior managers from 83 HEIs across 24 European countries	LA as an institutional capability shaped by organizational readiness and data availability	Identifies persistent barriers preventing LA from achieving full institutional decision impact
[49]	Statistics learning and instructional decision support	Integration of structured learner data and unstructured learning artifacts using machine learning	Heterogeneous data integration	Multi-source analytics enable richer diagnosis of engagement and help-seeking behavior
[50]	Online and blended learning environments; engagement-oriented course decisions	LMS data from 23 subjects, >5,500 enrolments, 406 staff roles, over five years	LMS data organized as institutional analytical assets	Teacher interaction positively influences engagement, whereas content overload may reduce engagement
[52]	VLE-based engagement monitoring	Machine learning using UK Open University VLE data	VLE logs as scalable analytics streams	Random Forest models achieved ~95% precision and ~98% relevance in early engagement prediction
[53]	E-learning personalization decisions	BI platform analysis of Blackboard LMS data (~600 samples within ~20,000 students)	BI–LMS integration for personalization support	Analytics-informed personalization improves learning experiences
[66]	Postsecondary early-risk prediction	Comparative evaluation of LMS-data contribution to prediction models	Marginal analytical value of LMS data	Early LMS activity can support prediction, but additional data do not always improve model quality
[6]	Classroom instructional decision-making with GenAI support	Multimodal LA involving 33 students, HRV/GSR data, AHP, and SAM	Integration of LA, biosignals, and ChatGPT	Multimodal analytics support richer instructional adaptation
[46]	Writing support and help-seeking decisions	Multimodal LA comparing ChatGPT and human expert support	GenAI as an additional learning-analytics data source	Reveals distinct help-seeking patterns relevant to support-system design

Platform-oriented analytics implementations further illustrate how institutional data ecosystems support personalization and instructional decision-making. An LMS-based analysis reported in [4] uses Blackboard interaction data within a BI analytics platform and derives insights from approximately 600 learners within a broader population of nearly 20,000 students during the 2022–2023 academic year. The findings suggest that analytics platforms can support personalization decisions when LMS data are systematically captured, integrated, and processed. At the same time, multimodal LA studies extend the scope of institutional data ecosystems by incorporating additional physiological and conversational data streams. Evidence from. [5] integrates LA, physiological signals (e.g., HRV and GSR), and ChatGPT-supported learning activities in a classroom setting involving 33 students, demonstrating that richer analytical ecosystems can support real-time instructional adaptation. Similarly, multimodal analytics research presented in [64] shows that GenAI-supported writing tasks generate additional behavioral and interaction data that reveal distinct help-seeking patterns compared with human-expert support.

4.1.2. Cross-Study Interpretation and Computational Implications

Collectively, these findings indicate that institutional data ecosystems constitute the foundational layer of analytics-enabled decision-making in higher education. However, the evidence also demonstrates that fragmentation, context dependence, and governance limitations continue to constrain scalability and institutional impact. Although predictive performance and analytical sophistication are frequently high, translating these capabilities into routine and institution-wide decision processes remains contingent on interoperability, data quality, governance maturity, and alignment with institutional workflows.

Cross-study comparison reveals a recurring trade-off. Multi-source and multimodal data ecosystems increase analytical richness and enable more precise diagnosis of student engagement, help-seeking behavior, and institutional performance. At the same time, this heterogeneity increases integration complexity, governance burden, and risks of inconsistent interpretation. Studies relying on LMS and VLE traces demonstrate strong scalability potential, but they frequently depend on platform-specific data structures that may not generalize across institutions or educational contexts. Consequently, the principal computational challenge extends beyond data availability toward the design of interoperable, governable, and institutionally sustainable analytical pipelines capable of supporting reliable decision-making across heterogeneous university systems.

Figure 3 conceptualizes institutional data ecosystems as socio-technical infrastructures that connect heterogeneous university systems, interoperability mechanisms, governance controls, and decision interfaces. The figure illustrates how fragmented platforms—including LMS, SIS, finance, human resources, library, and facilities-management systems—must be integrated through APIs, metadata standards, integration layers, and data warehouses before analytical outputs can support meaningful institutional decisions. Governance mechanisms, such as data stewardship, accountability structures, and access-control policies, are positioned as stabilizing components that support data reliability, transparency, and institutional trust. Collectively, the figure reinforces the broader argument of this review that analytics-enabled decision-making depends not only on technical integration, but also on governance structures and human interpretation capable of transforming fragmented institutional data into accountable and actionable decisions.

Figure 3. Data Ecosystems, Governance, and Interoperability in Higher Education.

Predictive learning-analytics studies further reinforce the importance of scalable and reliable analytical infrastructures. Using VLE data from the UK Open University, study [24] report strong predictive performance for early engagement detection, with Random Forest models achieving approximately 95% precision and up to 98% relevance. These findings demonstrate the technical feasibility of analytics-supported early-warning systems, while also highlighting the need for careful validation of transferability across disciplines, institutions, and platform ecosystems. Complementary work by [66] further cautions that larger volumes of data do not necessarily improve decision quality, emphasizing that the marginal contribution of LMS activity data must be empirically validated when developing early-risk prediction models in postsecondary settings.

4.2. Analytics Capability, BI Adoption, and Digital Readiness

This subsection distinguishes empirical evidence on analytics capability from the broader implications of capability development for analytics-enabled decision-making. Section 4.2.1 synthesizes evidence related to organizational and computational readiness, whereas Section 4.2.2 interprets how these readiness dimensions shape institutional decision value, analytics maturity, and capability sustainability.

4.2.1. Evidence Base and Key Patterns

The reviewed studies consistently show that analytics capability functions as a critical link between technical infrastructure and effective institutional decision-making. Across higher education contexts, BI and AI systems rarely improve decision quality in isolation; their institutional value depends heavily on analytical skills, governance structures, leadership support, digital readiness, and integration into organizational workflows. From a computing-oriented perspective, analytics capability should therefore be understood not only as organizational readiness, but also as the institutional capacity to operate, validate, govern, and sustain analytics pipelines over time.

Table 4 consolidates the reviewed evidence on analytics capability, BI adoption, and digital readiness, highlighting how organizational and computational readiness conditions influence analytics-enabled decision-making in higher education.

Table 4. Analytics capability, BI adoption, and digital readiness shaping decision effectiveness in higher education.

Refs.	Research Context (Higher Education Setting)	Capability / Readiness Focus	Methodology and Data Sources	Key Findings	Strengths / Limitations
[54]	Higher education institutions under Industry 4.0 pressures	Big Data Analytics Capability (BDAC) as organizational capability	SEM + ANN; empirical dataset (n = 83)	BDAC significantly improves institutional performance through data-driven decision pathways	Strong capability framing; limited operational detail on capability components
[55]	Saudi Arabian higher education; strategic decision-making	Organizational culture and socio-technical readiness	Cross-sectional quantitative survey	Culture-oriented readiness strengthens strategic decision value from analytics	Sample and effect-size details limited in abstract
[56]	Iraqi higher education institutions	Analytics adoption using TOE framework	Survey (n = 352); $R^2 = 0.514$	Technology, organization, and environment jointly explain analytics adoption	Limited evidence on post-adoption outcomes
[57]	University libraries in Pakistan	Digital readiness using UTAUT constructs	PLS-SEM; survey of 246 professionals	Performance expectancy and social influence drive big-data adoption	Context-specific to library environments
[7]	University libraries	Skills, workflows, and cultural readiness	Qualitative interviews (n = 25)	Analytics adoption reshapes evidence-based decision routines	Limited qualitative generalizability
[58]	Executive education and university leadership	Managerial analytics capability	Conceptual and curriculum-based analysis	Insight management is critical for decision quality	Limited empirical validation
[59]	Medical education students	User-level AI readiness	Survey (84/115 responses; 73.04% response rate)	Moderate readiness with persistent competency gaps	Domain-specific and self-reported
[60]	Higher education students (Industry 4.0 readiness)	Digital preparedness at individual and organizational levels	SEM with multidimensional instrument	Preparedness shaped by knowledge and organizational support	Sample size not fully reported
[61]	UAE higher education; HR decision-making	AI adoption readiness and organizational culture	Quantitative survey (n = 215)	Readiness and culture mediate sustainable institutional outcomes	Limited detail regarding AI tool categories

The reviewed literature consistently demonstrates that analytics-enabled decision-making in higher education is fundamentally shaped by institutional analytics capability and digital readiness rather than by technology availability alone. Across diverse higher education contexts, analytics capability is conceptualized as a multidimensional organizational construct encompassing infrastructure, analytical skills, leadership support, governance, organizational culture, and policy alignment. Quantitative evidence from multiple regions further indicates that when these dimensions remain underdeveloped or insufficiently aligned, BI and AI systems struggle to generate sustained institutional decision value even when technically implemented.

Capability-oriented empirical studies illustrate this pattern clearly. Evidence reported in [67], using a hybrid analytical approach that combines structural equation modeling and artificial neural networks across 83 higher education institutions, demonstrates that Big Data Analytics Capability (BDAC) functions as a significant driver of institutional performance through data-driven decision-making pathways. These findings reinforce the argument that analytics value emerges when technical resources are embedded within broader organizational capabilities rather than treated as standalone technologies. Similarly, findings presented in [68] show that organizational culture and socio-technical alignment substantially shape the strategic value derived from analytics adoption, emphasizing that leadership support, human readiness, and organizational alignment are essential complements to analytical infrastructures.

Adoption-oriented studies further highlight the importance of digital readiness and contextual constraints. Using the Technology–Organization–Environment (TOE) framework, the analysis conducted in [69] reports that technological, organizational, and environmental factors jointly explain analytics adoption intentions in Iraqi universities, with the proposed model accounting for 51.4% of variance ($R^2 = 0.514$) based on survey responses from 352 participants. These findings underscore the importance of infrastructure availability, institutional governance, and policy readiness in shaping analytics uptake.

In service-oriented higher education environments, evidence from [8] analyzes survey data from 246 university library professionals using PLS-SEM and demonstrates that performance expectancy and social influence—two core UTAUT dimensions—significantly influence big-data adoption within academic libraries. This evidence extends analytics capability discussions beyond central administration into distributed institutional units. Capability development is also strongly associated with human capital and leadership preparedness. Qualitative findings reported in [7], based on interviews across five stakeholder groups, indicate that analytics adoption in university libraries reshapes evidence-based decision routines and requires new competencies, workflow redesign, and cultural adaptation. Complementing this organizational perspective, prior work in [70] conceptualizes analytics capability as an executive competency, arguing that effective institutional decision-making depends on leaders' ability to translate analytical outputs into structured and actionable insights.

At the user level, readiness studies provide additional granularity. Empirical evidence from [71] reports moderate AI readiness among medical students, with response rates of 73.04% (84 of 115 invited participants) and mean readiness scores ranging from 3.52 to 3.90, suggesting that perceived opportunities frequently exceed actual analytical competency. Likewise, the structural equation modeling analysis presented in [30] demonstrates that student preparedness for Industry 4.0 technologies is jointly shaped by individual characteristics, technological knowledge, and organizational support structures.

Recent evidence further links analytics readiness with sustainable institutional outcomes. Drawing on survey data from 215 respondents in UAE higher education, findings reported in [61] demonstrate that AI adoption readiness and organizational culture jointly mediate the relationship between analytics usage and sustainable human-resource outcomes. Collectively, the evidence synthesized in Table 4 indicates that analytics capability operates as a holistic organizational capacity in which infrastructure and analytical tools are necessary but insufficient without aligned leadership, skills, governance, organizational culture, and policy readiness. These findings reinforce the broader argument advanced throughout this review that analytics maturity determines whether BI and AI systems function merely as reporting mechanisms or evolve into institutionally actionable decision-support infrastructures.

4.2.2. Cross-Study Interpretation and Capability Implications

Across this theme, analytics capability emerges as both an organizational and computational readiness construct. However, the reviewed studies differ substantially in how capability is operationalized. Some studies emphasize infrastructure and technology adoption, whereas others prioritize organizational culture, leadership, skills, governance, or policy readiness. This variation creates conceptual and measurement inconsistency, thereby limiting cross-study comparability and making institutional benchmarking more difficult.

From a computing-oriented perspective, analytics capability should be evaluated not only by the presence of BI or AI technologies, but also by the institution's ability to maintain data quality, manage model lifecycle processes, validate analytical outputs, monitor fairness and bias, and integrate analytics into routine decision workflows. These dimensions collectively determine whether analytical infrastructures can generate sustainable institutional value beyond isolated reporting functions.

Building on the cross-study synthesis, Figure 4 conceptualizes analytics capability as a multidimensional and socio-technical institutional construct rather than merely a technical asset. The framework integrates six interrelated dimensions—technical infrastructure, data quality, analytical skills, organizational culture, leadership support, and policy readiness—that collectively shape analytics maturity and decision effectiveness in higher education. The figure further illustrates how these dimensions evolve progressively and interactively, linking capability development with institutional outcomes such as improved strategic planning, operational efficiency, and evidence-informed governance.

Importantly, Figure 4 also highlights contextual modifiers—including regional disparities, institutional maturity, and resource constraints—that influence the pace and effectiveness of capability development. This representation aligns with the reviewed empirical evidence showing that investment in analytics technologies alone is insufficient to generate meaningful institutional decision support. Rather, sustainable analytics-enabled decision-making requires enterprise-wide commitment involving both technical infrastructures and human-centered organizational readiness.

Figure 4. Analytics capability, BI adoption, and digital readiness in higher education.

4.3. AI and Advanced Analytics for Decision Support

This subsection synthesizes evidence on AI and advanced analytics in higher education, followed by a discussion of their broader methodological, interpretability, and governance implications for analytics-enabled decision-making. Section 4.3.1 reviews the dominant AI/ML approaches and institutional decision domains, whereas Section 4.3.2 examines the methodological trade-offs shaping institutional value, scalability, explainability, and responsible deployment.

4.3.1. Evidence Base and Algorithmic Patterns

The reviewed studies indicate that AI and advanced analytics substantially expand the predictive and automation capabilities of higher education institutions while simultaneously introducing important methodological and governance trade-offs. Across instructional, managerial, operational, and strategic contexts, high model performance is frequently reported in academic-risk prediction, performance forecasting, admissions screening, and curriculum recommendation. However, the institutional value of these models depends not only on predictive accuracy, but also on validation design, contextual fit, explainability, fairness, and human oversight. To support the synthesis of algorithmic approaches and methodological trade-offs, Table 5 summarizes the AI/ML and advanced analytics techniques identified across higher education decision domains.

Table 5. AI/ML and advanced analytics methods for decision support across higher education domains

Refs.	Decision Domain and Use Case	AI/ML / Advanced Analytics Methods	Data Sources and Scale	Validation / Performance	Interpretability / HITL / Governance Considerations
[61]	Instructional; metacognitive support for online learners	Graph-based modeling with explainable AI; comparison with LSTM/RNN	Online learning traces from 49 learners	Improved predictive performance compared with baselines	Explainable AI supports interpretation of learner strategies
[62]	Instructional; dropout and retention-risk prediction	XGBoost, GBM, ANN, KNN, SVM, NB (10 algorithms)	482 students, 146 variables (2012–2022)	Accuracy 90.66%, F1-score 90.72, MSE 9.34, Log Loss 0.26	Highlights false-positive and interpretability concerns
[63]	Instructional; academic performance prediction	Data mining and predictive ML with K-fold cross-validation	1,468 undergraduate records	Accuracy 94.17%	Supports actionable early-risk identification
[64]	Instructional; learning-outcome prediction	ML using online-behavior features	661 courses with category-specific models	Accuracy ranges from 38.2% to 74.7% across course types	Highlights contextual sensitivity of models
[1]	Instructional and managerial; performance forecasting	Simulation-based ML with big-data analytics	>1,000 undergraduate records	Accuracy 95.5%	Limited interpretability discussion
[72]	Instructional; early-warning systems using real-time events	Real-time predictive analytics	Course-interaction event data	Early-identification focus	Supports instructor-in-the-loop monitoring
[66]	Instructional; evaluating LMS-data contribution	Comparative predictive modeling	LMS data stratified by student type and timing	Early LMS signals shown to be predictive	Supports data-governance and intervention-timing decisions
[73]	Instructional; bias-aware monitoring	Bias analysis with Optimal Time Index	Monitoring data with intervention at Day 60	Emphasizes fairness without sacrificing timeliness	Explicit governance-oriented framing
[74]	Operational; admissions screening	NLP with named-entity recognition (NER)	2,325 CVs	ROUGE-1 Recall 72.67%, ROUGE-2 Recall 74.32%; 3.84 s/CV	Human-in-the-loop admissions workflow
[75]	Managerial and instructional; curriculum and pathway recommendation	NLP with hybrid recommender systems	Evaluation involving 201 users	Positive user feedback	Supports strategic curriculum decisions

The evidence synthesized in this section indicates that AI and advanced analytics in higher education should be understood not merely as isolated applications, but as computational decision-support mechanisms with distinct methodological and governance characteristics. Across the reviewed studies, AI systems differ substantially in terms of data requirements, feature representation, model complexity, interpretability, scalability, validation rigor, and governance risk. These differences create important trade-offs between predictive performance, transparency, institutional deployability, and ethical accountability. Importantly, the quantitative performance metrics summarized in Table 5 should be interpreted cautiously because the reviewed studies employ different datasets, validation strategies, feature spaces, institutional contexts, and evaluation protocols; therefore, the reported results are intended to illustrate methodological diversity and general performance tendencies rather than provide direct cross-study benchmarking.

Four broad algorithmic paradigms can be identified across the reviewed literature. First, traditional machine-learning approaches—including decision trees, random forests, support vector machines, and gradient-boosting models—are widely used for academic-risk prediction and performance forecasting. Second, deep-learning models are applied when complex behavioral or temporal patterns must be captured, although they often introduce higher interpretability costs. Third, natural language processing (NLP) techniques support admissions screening, curriculum alignment, and analysis of textual learning artifacts. Fourth, GenAI extends analytics pipelines by producing explanations, feedback, and scenario-oriented outputs, while simultaneously introducing concerns regarding hallucination, accountability, and human verification.

4.3.2. Methodological Trade-Offs and Decision Implications

Cross-study comparison reveals several recurring methodological trade-offs. Models with higher predictive performance, particularly ensemble and boosting approaches, are often less transparent than simpler analytical models, thereby creating tension between accuracy and explainability. Studies using LMS and VLE data demonstrate strong scalability potential, but their transferability across institutional platforms and disciplinary contexts remains uncertain. Similarly, NLP- and GenAI-based systems offer substantial efficiency gains in text-intensive decision environments, yet their outputs frequently require human validation to reduce risks of misclassification, bias, and over-automation. These findings suggest that model selection in higher education should not be guided solely by predictive accuracy, but also by interpretability, fairness, intervention timing, data availability, governance readiness, and institutional capacity for responsible deployment.

Instructional decision-making dominates the empirical landscape. Multiple large-scale predictive studies report strong model performance when machine learning is applied to academic and behavioral data. Empirical evidence reported by [76], evaluating ten algorithms using 482 student records and 146 variables spanning a ten-year period, indicates that XGBoost achieved cross-validated accuracy of 90.66% and an F1-score of 90.72, with low error rates (MSE = 9.34; Log Loss = 0.26). Similarly, findings presented in [77], using 1,468 undergraduate records with K-fold cross-validation, report prediction accuracy of 94.17% for academic-performance forecasting. Related work in [78] further reports prediction accuracy of 95.5% using behavioral data from more than 1,000 undergraduate students. Collectively, these findings demonstrate the strong technical feasibility of AI-driven prediction for instructional decision support.

At the same time, the reviewed studies consistently indicate that predictive performance alone is insufficient for effective institutional decision-making. Research presented in [7] explicitly incorporates explainable AI to reveal learner-strategy patterns among 49 online learners, demonstrating how interpretability supports human judgment and targeted intervention beyond black-box prediction. Likewise, evidence synthesized from [79], analyzing 661 courses across multiple categories, reports substantial variation in predictive accuracy (38.2%–74.7% across course types), highlighting the contextual sensitivity of AI performance across disciplinary environments. These findings reinforce the socio-technical arguments advanced in Section 3 regarding the importance of contextual reasoning, validation, and human oversight.

Operational and managerial decision-support applications further extend the role of AI in higher education. An evaluation conducted in [65] assesses an NLP-based admissions-screening system using 2,325 CVs and reports ROUGE-1 recall of 72.67%, ROUGE-2 recall of 74.32%, and processing times of 3.84 seconds per CV, illustrating substantial efficiency gains in high-volume operational settings. Similarly, findings reported in [13] demonstrate how NLP-based recommender systems, evaluated using 201 student and faculty users, can support curriculum alignment and learning-pathway design in response to labor-market demands.

Additional studies emphasize the importance of intervention timing, governance, and fairness considerations. Evidence from [72] and [4] shows that early-course LMS signals can support timely interventions while simultaneously raising questions regarding data minimization, fairness, and governance. Related work in [66] explicitly addresses these concerns through bias-aware monitoring and the introduction of an Optimal Time Index (Day 60) for intervention, emphasizing the ethical and governance dimensions of AI-supported decision-making.

Overall, the findings synthesized in Table 5 demonstrate that AI and advanced analytics provide substantial gains in predictive accuracy, scalability, and operational efficiency across university decision domains. However, consistent with the socio-technical perspectives developed throughout this review, their institutional decision value ultimately depends on interpretability, governance mechanisms, contextual validation, and HITL integration capable of ensuring fairness, legitimacy, and responsible deployment.

Building on this computational synthesis, Figure 5 presents a taxonomy of analytics techniques across higher education decision contexts. The figure classifies the reviewed approaches into descriptive, predictive, prescriptive, and generative analytics, and maps these categories to instructional, managerial, operational, and strategic decision domains. This taxonomy clarifies that analytics-enabled decision-making extends beyond dashboards and predictive models toward a broader ecosystem of computational approaches characterized by different strengths, risks, and governance requirements.

Figure 5. Taxonomy of analytics techniques and decision contexts in higher education.

4.4. Human-in-the-Loop Decision Routines and Institutional Outcomes

This subsection distinguishes the empirical evidence on GenAI and HITL practices from the broader operational interpretation of HITL as a decision-control mechanism. Section 4.4.1 synthesizes the reviewed evidence on GenAI-supported and human-mediated decision routines, while Section 4.4.2 discusses the governance and operational implications of HITL integration for analytics-enabled decision-making in higher education.

4.4.1. Evidence Base and HITL Patterns

A central insight emerging from this theme is that HITL mechanisms transform analytical outputs into legitimate institutional decisions. Dashboards, predictive models, and GenAI-generated recommendations become institutionally meaningful only when human actors interpret, validate, contextualize, and operationalize these outputs within organizational workflows. Across the reviewed studies, HITL routines are particularly important in high-stakes contexts such as assessment, admissions, curriculum management, and academic intervention, where fairness, trust, accountability, and contextual reasoning cannot be delegated entirely to automated systems. Table 6 summarizes the reviewed evidence on GenAI-supported analytics and HITL decision routines, with emphasis on how human validation, governance structures, and ethical safeguards mediate institutional outcomes.

Across the reviewed studies, a recurring pattern is that the institutional value of analytics, business intelligence, and GenAI emerges most effectively when these technologies are embedded within HITL decision routines. Across instructional, managerial, and administrative contexts, AI systems are consistently positioned as decision-support mechanisms whose outputs require human interpretation, contextualization, and validation to ensure legitimacy, fairness, and institutional appropriateness.

The reviewed studies further demonstrate that HITL integration operates not merely as an ethical safeguard, but also as an operational requirement for reliable analytics-enabled decision-making. In assessment and feedback contexts, educators play a central role in validating and refining AI-generated outputs before institutional deployment. For example, findings reported in [67] demonstrate that large language model (LLM)-supported feedback systems can scale assessment processes to approximately 22,000 submissions annually while still requiring educator review to maintain reliability and consistency.

Table 6. GenAI and Human-in-the-Loop (HITL) Decision Routines and Institutional Outcomes in Higher Education.

Refs.	GenAI / AI Use Case	Decision-Routine Stages Emphasized	HITL Mechanisms	Governance / Ethical Controls
[67]	LLM-supported assessment feedback (code and narrative)	Feedback generation → review → release	Educators validate and refine AI-generated feedback	Reliability and transparency safeguards
[64]	GenAI-supported writing and help-seeking analysis	Interpretation → intervention design	Human interpretation of multimodal analytics	Trust calibration and responsible-use mechanisms
[5]	ChatGPT-integrated classroom analytics	Monitoring → interpretation → pedagogical adjustment	Instructor-in-the-loop analytics use	Data integration and transparency considerations
[36]	Detection of AI-generated admissions materials	Screening → verification → adjudication	Human review of flagged applications	Fairness, accountability, and auditability
[31]	GenAI-supported visualization learning	Learning support → feedback → evaluation	Instructor-led scaffolding	Responsible AI use in learning
[80]	Bias detection in admissions letters	Evaluation → deliberation → selection	Human reviewer awareness and training	Equity and bias-governance mechanisms

Similarly, classroom-level studies emphasize the importance of instructor interpretation in AI-supported pedagogical environments. Evidence presented in [5] integrates ChatGPT-supported LA within classroom activities and shows that instructors remain central to interpreting dashboards, contextualizing learner behavior, and adjusting pedagogical interventions. Complementary findings from [64] further demonstrate that GenAI-mediated help-seeking behaviors differ substantially from interactions involving human experts, suggesting that multimodal analytics outputs require contextual human interpretation before informing institutional support decisions.

The reviewed literature also highlights the increasing importance of HITL governance in high-stakes administrative processes. Research proposed in [36] introduces an AI-assisted detection framework for identifying AI-generated admissions materials and emphasizes that automated screening must remain coupled with human adjudication to reduce false positives and preserve procedural trust. Likewise, evidence synthesized in [80], analyzing approximately 4,000 admissions applications, demonstrates that analytics-supported bias detection improves fairness only when reviewers are trained to recognize, interpret, and respond to algorithmically identified bias patterns.

Collectively, these findings indicate that HITL routines serve as institutional mechanisms for aligning computational outputs with ethical standards, organizational values, and contextual judgment. Rather than replacing human expertise, analytics and GenAI systems appear to function most effectively when integrated into collaborative socio-technical workflows that preserve human oversight, accountability, and institutional legitimacy.

4.4.2. Operational Decision Routines and Governance Implications

From an operational perspective, HITL decision routines can be conceptualized as a cyclical process consisting of four interrelated stages: algorithmic output generation, human interpretation, contextual validation, and decision feedback. In the first stage, analytics dashboards, predictive models, or GenAI systems generate recommendations, alerts, or analytical outputs. In the second stage, faculty members, administrators, or managers interpret these outputs in relation to institutional context and domain expertise. The third stage involves contextual validation, where human actors assess whether recommendations are fair, appropriate, explainable, and actionable. Finally, decision outcomes are reintegrated into the analytics pipeline through monitoring, evaluation, and feedback-based refinement. This operational cycle transforms HITL from a broad ethical principle into a concrete decision-control mechanism that links analytics outputs to accountable institutional action.

Several reviewed studies reinforce this governance-oriented interpretation of HITL integration. Although the study presented in [67] is not situated directly within higher education, it provides a relevant methodological illustration for the present review's computing-oriented perspective. The study combines hourly weather data, EnergyPlus simulations, and comparative LSTM and Random Forest models to support climate-based building-energy forecasting. Importantly, the study emphasizes validation procedures, feature-importance analysis, uncertainty assessment, and human-supervised deployment, demonstrating that predictive systems should be evaluated not only by performance metrics but also by interpretability, governance readiness, and deployment reliability.

Similarly, findings reported in [31], based on a three-week evaluation involving 65 graduate students, demonstrate that GenAI-supported visualization learning is most effective when instructors actively guide interpretation, monitor learner progress, and adapt instructional scaffolding. These findings reinforce the broader argument that AI systems produce institutional value primarily when embedded within supervised and context-aware decision workflows.

Taken together, the findings synthesized in Table 6 indicate that sustainable institutional outcomes—including instructional quality, scalable assessment, fairness in admissions, and trustworthy analytics-enabled governance—emerge from socio-technical decision systems rather than from automation alone. Consistent with the theoretical perspectives outlined in Sections 1 and 3, HITL governance structures function as critical guardrails that align analytics and AI capabilities with institutional values, ethical accountability, and contextual human judgment. Building on this synthesis, Figure 6 visualizes HITL as a cyclical decision routine connecting algorithmic outputs, human interpretation, contextual validation, institutional action, and feedback-based refinement.

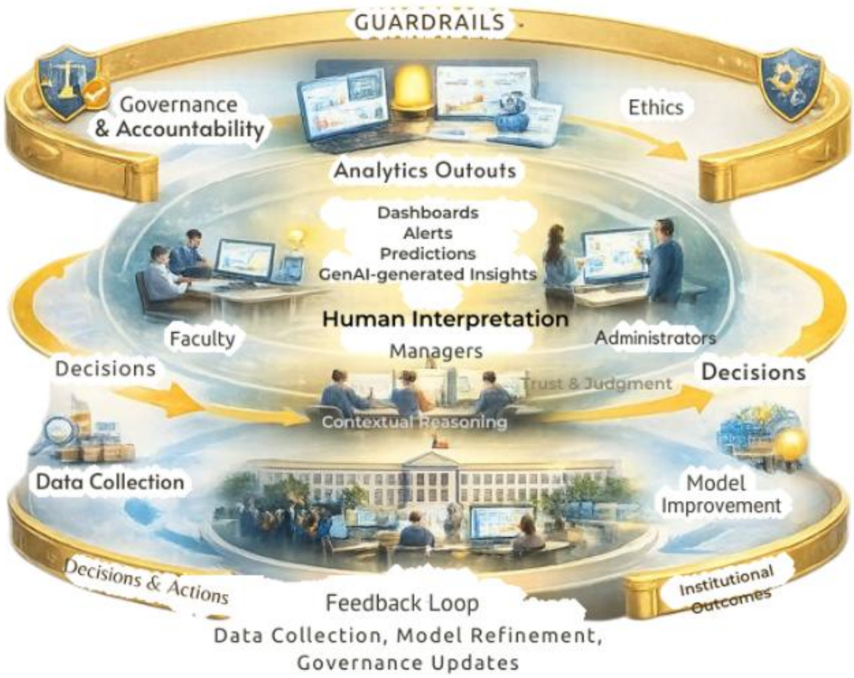

Figure 6. Human-in-the-Loop Decision Routines and Institutional Outcomes.

4.5. Taxonomy of Analytics Techniques across Decision Contexts

This subsection presents the taxonomy of analytics techniques as an integrative synthesis of the preceding thematic findings. It first defines the major categories of analytics approaches identified across the reviewed studies and then discusses how these categories differ in terms of computational orientation, decision context, methodological strengths, limitations, and governance implications.

4.5.1. Analytics Categories and Decision Contexts

To strengthen the computing-oriented contribution of this review, the synthesized literature can be organized into four broad categories of analytics techniques: descriptive analytics, predictive analytics, prescriptive analytics, and generative analytics. This taxonomy clarifies that analytics-enabled decision-making in higher education is not a single methodological paradigm, but rather a spectrum of computational approaches characterized by different data requirements, model architectures, interpretability levels, operational purposes, and governance considerations.

Across the reviewed studies, descriptive analytics is primarily associated with dashboard-oriented monitoring and institutional reporting; predictive analytics focuses on forecasting and risk estimation; prescriptive analytics extends prediction into intervention and decision recommendation; while generative analytics introduces explanation, content generation, and scenario-oriented decision support through large language models and GenAI systems. By organizing the reviewed evidence into these categories, the taxonomy highlights how different analytics paradigms support distinct instructional, managerial, operational, and strategic decision contexts within higher education institutions.

4.5.2. Strengths, Limitations, and Governance Implications

Descriptive analytics, commonly implemented through BI dashboards, KPI reporting systems, and visualization tools, primarily supports institutional visibility into student engagement, operational performance, resource utilization, and organizational monitoring. These approaches are generally highly interpretable and accessible for institutional stakeholders; however, they often remain limited to descriptive reporting and may provide relatively weak support for actionable intervention.

Predictive analytics, typically implemented through machine-learning techniques such as decision trees, random forests, gradient boosting, support vector machines, and neural networks, supports early-warning systems, dropout prediction, academic-risk identification, and performance forecasting. These models offer substantial anticipatory decision-support capability and frequently demonstrate strong predictive performance. Nevertheless, the reviewed studies consistently highlight challenges related to explainability, fairness, transferability, validation rigor, and governance readiness.

Table 7. Taxonomy of analytics techniques and decision contexts in higher education.

Analytics Category	Typical Techniques	Main Data Sources	Typical Decision Contexts	Strengths	Key Limitations
Descriptive analytics	BI dashboards, KPI reporting, visualization systems, statistical summaries	LMS, SIS, finance, HR, library, and administrative records	Student-engagement monitoring, institutional reporting, operational monitoring	High interpretability and strong monitoring capability	Often limited to reporting and weak actionability
Predictive analytics	Decision trees, random forests, gradient boosting, SVM, neural networks, early-warning models	LMS/VLE logs, grades, demographic data, behavioral traces	Academic-risk prediction, dropout forecasting, performance prediction	Strong anticipatory decision-support capability and high predictive potential	Transferability, bias, explainability, and validation challenges
Prescriptive analytics	Recommender systems, optimization models, intervention rules, decision policies	Integrated student, curriculum, and institutional data	Academic advising, curriculum redesign, resource allocation	Connects prediction to institutional action	Requires strong governance, contextual validation, and workflow integration
Generative analytics	LLMs, GenAI-based feedback generation, text generation, explanation systems, scenario generation	Textual submissions, prompts, interaction logs, institutional documents	Feedback generation, decision explanation, scenario exploration	Scalable interpretive support and adaptive interaction	Hallucination risk, opacity, accountability concerns, and human-verification requirements

Prescriptive analytics extends predictive insights into recommended institutional actions through optimization models, recommender systems, intervention rules, and decision-policy mechanisms. Compared with descriptive and predictive approaches, prescriptive analytics moves closer to operational decision execution by linking predictions to concrete institutional responses. However, these systems require stronger governance structures, contextual validation, and human oversight to ensure institutional appropriateness and accountability.

Generative analytics, enabled by large language models and GenAI systems, introduces a newer layer of analytics-enabled decision support by generating explanations, summaries, feedback, recommendations, and scenario-oriented outputs. Across the reviewed literature, generative analytics demonstrates strong potential for scalable interpretive support and human-centered interaction. At the same time, these systems raise important concerns regarding hallucination, opacity, accountability, reliability, and the need for human verification mechanisms. Building on the preceding synthesis, Table 7 classifies analytics techniques according to their computational orientation, primary data sources, decision contexts, methodological strengths, and governance-related limitations.

4.6. End-to-End Computational Pipeline for Analytics-Enabled Decision-Making

The reviewed studies can be synthesized into an end-to-end computational pipeline that explains how analytics systems operationalize decision-making in higher education institutions. This pipeline conceptualizes analytics-enabled decision-making as a continuous socio-technical process consisting of seven interconnected stages: data acquisition, preprocessing and integration, feature construction, modeling and analytics, decision interface, HITL validation, and feedback-based refinement.

Building on the synthesized findings across Sections 4.1–4.5, the reviewed studies can be synthesized into an end-to-end computational pipeline that explains how analytics systems operationalize decision-making in higher education institutions. This pipeline-oriented perspective moves the discussion beyond application-level descriptions toward a system-level understanding of how LA, BI, AI, and GenAI collectively function as institutional decision-support infrastructures.

The first stage, data acquisition, involves collecting heterogeneous institutional and learning data from learning management systems (LMS), student information systems (SIS), virtual learning environments (VLE), assessment platforms, admissions systems, library services, administrative databases, and increasingly multimodal or GenAI-mediated interactions. The second stage, preprocessing and integration, transforms fragmented data into usable analytical datasets through cleaning, normalization, metadata management, interoperability mechanisms, and integration workflows such as APIs, ETL/ELT pipelines, and data warehouses.

The third stage, feature construction, converts raw institutional data into meaningful analytical variables and indicators, including engagement frequency, submission behavior, academic performance trajectories, risk indicators, and institutional KPIs. The fourth stage, modeling and analytics, applies descriptive, predictive, prescriptive, or generative analytical approaches depending on the institutional decision objective. Descriptive models support monitoring and reporting; predictive models support early warning and forecasting; prescriptive models support intervention and recommendation; while generative models support explanation, feedback generation, and scenario-oriented decision support.

The fifth stage, decision interface, translates analytical outputs into actionable forms such as dashboards, alerts, recommendation systems, reports, or GenAI-generated explanations that can be interpreted by institutional stakeholders. The sixth stage, HITL validation, ensures that faculty members, administrators, or institutional decision-makers evaluate the fairness, contextual appropriateness, interpretability, and ethical implications of analytical outputs before action is taken. The final stage, feedback-based refinement, incorporates institutional outcomes back into the analytics ecosystem through model recalibration, governance revision, performance monitoring, audit logging, and iterative improvement of decision workflows.

Collectively, this pipeline demonstrates that analytics-enabled decision-making is not completed when a dashboard displays an indicator or when a predictive model generates an output. Institutional decision value emerges when computational outputs are embedded within accountable workflows that connect data ecosystems, analytical models, governance structures, human judgment, institutional action, and feedback-driven refinement. Accordingly, universities should evaluate analytics systems not only in terms of predictive accuracy or visualization capability, but also in relation to interoperability, explainability, governance readiness, decision integration, and post-deployment learning capacity.

Figure 7 presents the proposed end-to-end computational pipeline, illustrating how institutional data are transformed into accountable decision support through analytics, human validation, governance mechanisms, and feedback-based refinement.

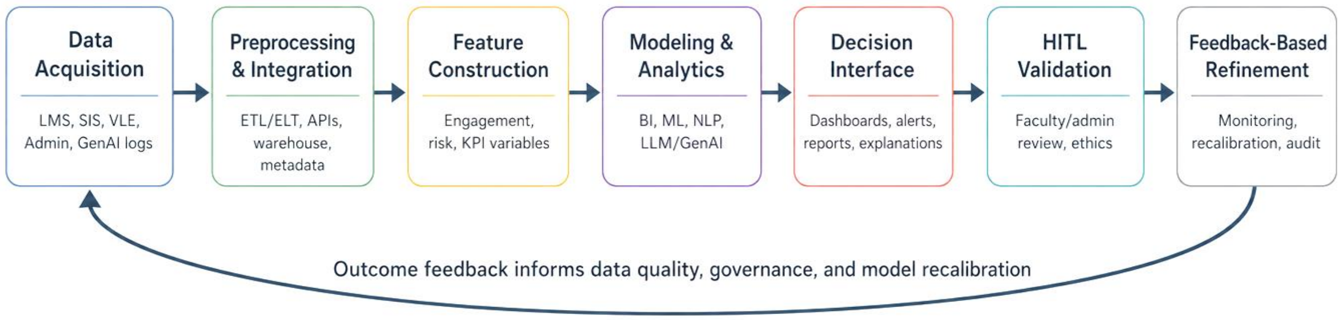

Figure 7. End-to-end computational pipeline for analytics-enabled decision-making in universities.

The operational stages of the proposed computational pipeline are summarized in Table 8, which links each stage to its primary computing components and institutional decision relevance.

Table 8. End-to-end computational pipeline for analytics-enabled decision-making in universities

Pipeline Stage	Main Function	Typical Computing Components	Decision Relevance
Data acquisition	Collect institutional and learning data	LMS, SIS, VLE, admissions systems, HR, finance, library systems, GenAI interaction logs	Determines data coverage and institutional decision scope
Preprocessing and integration	Clean, harmonize, and integrate heterogeneous data	ETL/ELT workflows, APIs, data warehouses, metadata standards, data-quality mechanisms	Determines interoperability, consistency, and reliability
Feature construction	Transform raw data into analytical variables and indicators	Engagement features, behavioral patterns, risk indicators, KPI variables	Determines analytical relevance and interpretability
Modeling and analytics	Generate predictions, insights, recommendations, or explanations	BI systems, ML models, NLP, recommender systems, optimization methods, LLMs/GenAI	Determines analytical capability and methodological trade-offs
Decision interface	Present analytical outputs to institutional users	Dashboards, alerts, reports, recommendation interfaces, GenAI explanations	Determines usability, accessibility, and actionability
Human-in-the-loop validation	Interpret, contextualize, and validate outputs	Faculty review, administrator oversight, ethics review, expert judgment	Determines legitimacy, fairness, and accountability
Feedback-based refinement	Monitor outcomes and improve analytical systems	Model recalibration, audit logs, governance updates, performance monitoring	Determines long-term adaptation, learning, and sustainability

4.7. Summary of Synthesized Findings

This review synthesized evidence on how LA, BI, AI, and GenAI support decision-making in higher education institutions, while also investigating why their institutional impact often remains limited despite increasing technological sophistication. Synthesizing evidence across data ecosystems, analytics capability, advanced AI applications, HITL decision routines, and end-to-end computational pipelines, the review demonstrates that analytics-enabled decision-making in universities is fundamentally a socio-technical and computing-oriented process rather than a purely technological one.

To make the synthesized findings more explicit and analytically visible, Table 9 reorganizes the main findings into four dimensions: the core synthesized insight, converging or diverging evidence patterns, the primary trade-off or limitation, and the resulting institutional decision implication. This structure emphasizes the central contributions of the review more clearly and highlights why these findings matter for universities seeking to move beyond dashboard-oriented reporting toward accountable and decision-oriented analytics infrastructures.

The central message emerging from Table 9 is that analytics initiatives should not be evaluated primarily in terms of technology adoption, dashboard availability, or predictive accuracy alone. Their institutional value depends on whether data ecosystems, analytical models, governance mechanisms, decision interfaces, human validation routines, and feedback loops are aligned within accountable institutional decision processes. This synthesis clarifies why moving beyond dashboards requires universities to invest in decision infrastructure rather than merely deploying analytical technologies.

Table 9. Core synthesized insights, evidence patterns, trade-offs, and decision implications

Core Synthesized Insight	Converging / Diverging Evidence and Representative Support	Key Limitation or Trade-Off	Decision Implication
Governed data ecosystems constitute the foundation of analytics-enabled decision-making.	Prior reviews and platform-oriented studies consistently emphasize the importance of provenance, data quality, metadata standards, interoperability, ETL processes, consent management, and KPI alignment [13], [19], [20], [22], [23], [81].	Increasing data richness improves analytical insight but simultaneously increases interoperability, governance, and integration complexity.	Universities should prioritize governance, interoperability, and data-quality infrastructure before scaling dashboards or predictive analytics initiatives.
Analytics capability transforms technical infrastructure into institutional decision value.	Capability-oriented studies converge on the importance of data platforms, analytical skills, leadership support, workflow integration, and knowledge management [2], [15], [26], [29].	Dashboards and BI tools provide visibility but do not ensure institutional uptake without organizational and computational readiness.	Analytics maturity should be evaluated as both organizational and computational readiness rather than by technology availability alone.
AI and GenAI systems must be evaluated beyond predictive accuracy.	Studies report substantial gains from ML, NLP, and GenAI applications, but diverge in terms of explainability, validation rigor, portability, calibration, fairness, and monitoring practices [1], [16], [23], [35].	High predictive performance may obscure bias, weak calibration, poor interpretability, and deployment-related risks.	Universities should evaluate AI systems using fairness, robustness, interpretability, governance, privacy, and post-deployment monitoring criteria in addition to accuracy metrics.
Human-in-the-loop routines transform analytical outputs into legitimate institutional decisions.	Governance-oriented studies consistently support expert review, multidisciplinary oversight, contextual validation, and continuous monitoring, although implementation remains uneven across institutions [9], [19], [20], [34], [35].	Automation improves scalability and efficiency but cannot replace contextual reasoning, ethical judgment, or institutional legitimacy.	Human oversight and accountability mechanisms should be formalized as integral components of analytics-enabled decision workflows.
Decision intelligence requires end-to-end computational pipelines.	Platform and governance studies demonstrate greater institutional value when data ingestion, integration, validated models, interfaces, monitoring, and feedback mechanisms are operationally connected [16], [22], [23], [35].	Dashboards and predictive models remain limited when disconnected from institutional workflows and outcome-feedback processes.	Analytics systems should be designed as accountable decision infrastructures rather than isolated technical tools or reporting interfaces.

Taken together, the reviewed evidence indicates that robust data ecosystems and advanced analytical models are necessary but insufficient conditions for effective institutional decision-making. Institutional outcomes improve most consistently when analytics capabilities are embedded within mature organizational environments characterized by interoperable systems, governance readiness, skilled personnel, supportive leadership, and cultures that value evidence-informed practice. Although AI and GenAI applications provide substantial gains in prediction, automation, personalization, and operational efficiency, their institutional value remains constrained by interpretability challenges, contextual variability, ethical risks, and limited post-deployment monitoring.

HITL configurations therefore emerge as a critical mechanism for aligning analytical outputs with professional judgment, institutional accountability, and contextual decision-making, particularly in high-stakes educational settings. Across the reviewed literature, sustainable and trustworthy analytics-enabled decision-making consistently depends on the interaction between computational capability, governance structures, and human oversight rather than on automation alone.

Overall, this review contributes to the literature by integrating previously fragmented research streams into a coherent computing-oriented framework explaining how analytics move from data acquisition to institutional decision-making in higher education. The review also identifies persistent gaps related to governance maturity, cross-institutional comparability, model portability, post-deployment evaluation, and feedback-driven refinement. Addressing these challenges is essential for universities seeking to implement analytics, BI, AI, and GenAI responsibly, sustainably, and accountably. Ultimately, moving beyond dashboards requires rethinking analytics not as isolated technological tools, but as components of human-centered and governance-aware decision ecosystems that balance technological innovation with institutional accountability and ethical responsibility.

5. Discussion

The findings synthesized across Sections 4.1–4.7 collectively reinforce the central argument of this review: analytics-enabled decision-making in higher education generates meaningful institutional value only when technological capabilities are embedded within mature organizational, governance, and human-centered systems. Evidence summarized in Table 3 demonstrates that although universities increasingly possess rich data ecosystems and advanced learning-analytics infrastructures, fragmentation, interoperability limitations, and uneven data quality continue to constrain the translation of analytics into routine and reliable institutional decision-making. These findings support earlier observations regarding the persistent insight–action gap identified in Section 1, particularly when governance structures and institutional decision processes remain insufficiently developed.

Building on this foundation, the evidence synthesized in Table 4 provides strong support for the role of analytics capability and digital readiness as critical mediators between BI/AI adoption and institutional decision quality. Across the reviewed studies, investments in infrastructure and analytical technologies yield limited impact without complementary development of analytical skills, leadership support, organizational culture, governance readiness, and workflow integration. This capability-oriented interpretation aligns with empirical frameworks linking analytics maturity, integrated data ecosystems, and improved decision outcomes across sectors [8], while extending these perspectives to higher education environments. Institutions demonstrating higher levels of analytical maturity and organizational readiness are consistently better positioned to leverage analytics for strategic planning, operational efficiency, and student success, including improvements in retention and satisfaction outcomes [32].

5.1. Computing-Oriented Contribution and Novelty

The synthesis indicates that the primary contribution of this review lies not merely in aggregating studies on LA, BI, AI, and GenAI, but in integrating them into a computing-oriented decision-intelligence perspective. Across the reviewed literature, analytics systems vary substantially in terms of data architecture, algorithmic paradigms, validation strategies, explainability mechanisms, governance structures, and human oversight practices. These variations help explain why similar technologies often produce substantially different institutional outcomes across universities, depending on how analytical systems are designed, validated, governed, and embedded within institutional decision routines.

Unlike prior reviews that primarily emphasize technology adoption, dashboard implementation, or isolated AI applications, this review conceptualizes analytics-enabled decision-making as an end-to-end socio-technical pipeline connecting data ecosystems, computational models, governance mechanisms, and human interpretation. This perspective extends the discussion beyond application-level comparisons toward a system-level understanding of how universities operationalize analytics as accountable decision-support infrastructures.

5.2. From Dashboards to Decision Intelligence

The findings also challenge dashboard-centric assumptions that continue to shape much of the higher education analytics literature. Dashboards remain useful as visualization and monitoring interfaces; however, they do not independently constitute decision intelligence. Rather, decision intelligence requires a complete socio-technical and computational pipeline involving reliable data acquisition, integration, model development, validation, explainability, human interpretation, accountable action, and feedback-driven refinement.

Accordingly, moving beyond dashboards should not be understood merely as a transition from descriptive visualization toward predictive analytics. Instead, it represents a broader transition from reporting-oriented systems toward governed, adaptive, and institutionally integrated decision-support infrastructures. This interpretation helps explain why many universities continue to experience limited institutional impact despite increasing investments in analytical technologies and predictive modeling capabilities.

5.3. Methodological and Practical Implications

The review further demonstrates that advanced AI and machine-learning approaches substantially improve predictive accuracy, scalability, and operational efficiency across instructional, managerial, and operational decision domains. However, these gains remain highly context-dependent and are frequently accompanied by reduced interpretability, governance complexity, and increased ethical risk. Variability in model performance across courses, disciplines, institutions, and deployment settings underscores the importance of contextual calibration and cautions against the uncritical transfer of AI-driven solutions between educational environments.

These findings align with emerging governance-oriented perspectives emphasizing accountability, transparency, explainability, and ethical oversight as prerequisites for responsible analytics deployment [21], [70]. The reviewed evidence consistently indicates that predictive accuracy alone is insufficient as a measure of institutional decision value. Instead, analytics systems must also be evaluated in terms of robustness, fairness, interpretability, governance readiness, and post-deployment sustainability.

Crucially, the evidence synthesized in Table 6 positions HITL decision routines as a central mechanism connecting analytics capability to legitimate and sustainable institutional outcomes. Across assessment, admissions, curriculum design, intervention planning, and learning-support contexts, the reviewed studies consistently demonstrate that professional expertise, contextual reasoning, and human judgment remain indispensable for interpreting analytics outputs and mitigating risks related to bias, fairness, opacity, and institutional trust. This socio-technical interpretation aligns closely with the theoretical foundations discussed in Section 3, particularly regarding the limitations of purely algorithmic decision-making and the continuing importance of preserving human agency in high-stakes educational environments.

5.4. Limitations and Future Research

The discussion also highlights several moderating factors influencing analytics effectiveness, including regional disparities, institutional maturity, governance readiness, and resource availability [82], [83]. Well-resourced and analytically mature institutions generally demonstrate greater capacity to operationalize analytics effectively than less mature counterparts, suggesting that analytics strategies should be context-sensitive rather than universally prescribed.

Despite substantial progress in analytics-enabled decision-making research, several important gaps remain unresolved. Longitudinal evidence regarding the sustained institutional impact of analytics initiatives remains limited, governance practices continue to be unevenly theorized and empirically evaluated, and cross-institutional comparability is constrained by inconsistent metrics, reporting standards, and validation practices [1], [7], [8] Future research should therefore prioritize longitudinal and comparative designs, stronger governance and ethical evaluation frameworks, and the development of human-centered and GenAI-aware decision-support systems.

Several unresolved gaps are particularly important from a computational and methodological perspective. First, evidence regarding model portability across institutions, platforms, and disciplinary contexts remains limited. Second, many studies continue to report predictive performance without sufficiently documenting feature engineering, validation design, bias monitoring, calibration procedures, or post-deployment evaluation. Third, GenAI-supported decision systems remain under-evaluated with respect to hallucination risk, accountability, auditability, and governance oversight. Fourth, relatively few studies examine the complete lifecycle of analytics-enabled decision-making, from data generation and integration to institutional action and feedback-driven refinement. Collectively, these limitations suggest that future research should evaluate analytics systems not as isolated applications or predictive models, but as operational decision pipelines embedded within broader socio-technical and governance ecosystems.

6. Conclusion

This review contributes to the higher education analytics literature by advancing a computing-oriented decision-intelligence perspective that integrates learning analytics, BI, AI, and GenAI within a unified socio-technical framework. Rather than treating analytics systems as isolated dashboards or predictive tools, the review conceptualizes them as interconnected decision-support infrastructures involving data integration, analytical modeling, governance, explainability, human validation, and feedback-driven refinement. The synthesis further suggests that the long-term institutional value of analytics depends not only on predictive capability, but also on interoperability, governance maturity, contextual adaptation, and sustained human oversight. Accordingly, universities seeking to move beyond dashboard-centric practices should prioritize accountable decision infrastructures that connect analytical outputs with institutional workflows, governance processes, and continuous organizational learning.

The review contributes a computing-oriented decision-intelligence framework that conceptualizes analytics-enabled decision-making as a multi-layer socio-technical pipeline involving data acquisition, preprocessing and integration, feature construction, modeling and analytics, explainability, governance, decision execution, human validation, and feedback-based refinement. This framework extends prior review streams by shifting the focus from technology adoption and isolated applications toward system-level analytical infrastructures, methodological trade-offs, and operational decision processes.

The findings further indicate that universities should evaluate analytics systems not solely on the basis of predictive accuracy, dashboard sophistication, or AI adoption rates, but also in terms of interoperability, governance maturity, interpretability, accountability, workflow integration, and long-term institutional sustainability. In this context, HITL governance emerges as a critical mechanism for ensuring that analytics and AI systems remain aligned with institutional values, contextual judgment, and ethical responsibility.

Future research should move beyond reporting predictive performance or adoption intention and instead examine the full operational lifecycle of analytics systems in higher education. Particular attention should be directed toward model portability, post-deployment monitoring, fairness evaluation, GenAI accountability, governance maturity, and comparative institutional analysis across diverse educational contexts. From a practical perspective, the findings suggest that universities should approach LA, BI, AI, and GenAI not as standalone technologies, but as governed decision-support infrastructures requiring sustained organizational readiness, technical reliability, ethical oversight, and continuous human judgment.

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