UNIVERSITY PROFESSORS' FAVORABLE DISPOSITION TOWARD AI-BASED DIAGNOSTIC ASSESSMENT: CHALLENGES AND OPPORTUNITIES FOR FACULTY DEVELOPMENT

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ABSTRACT
Background: The integration of artificial intelligence (AI) into university diagnostic assessment raises concerns about the dehumanization of pedagogical practices. Objectives: This theoretical-conceptual contribution examines the transition from traditional evaluation models to AI-assisted frameworks, identifying faculty development as a key driver of educational change. Methods: Through a critical synthesis of international literature, the study explores training models that reframe AI from a "threatening agent" to a "cognitive and affective scaffold." Results: The paper proposes a four-phase conceptual model of algorithmic scaffolding that transforms Learning Management System (LMS) data into insights supporting teachers' reflective practices. AI's potential remains conditional upon data quality, algorithmic transparency, and professional interpretation. Conclusions: Conceived as a collaborative tool rather than a substitute for human judgment, AI may help university teachers personalize learning pathways, strengthen pedagogical relationships, and promote inclusive higher education.

KEYWORDS
Faculty development; faculty readiness; diagnostic assessment; higher education.

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1. Introduction

The integration of Artificial Intelligence (AI) systems within the higher education landscape has triggered an epistemological, ethical, and methodological debate on a global scale (Crompton & Burke, 2023; Zawacki-Richter et al., 2019). If, on the one hand, technological innovation offers unprecedented tools for the optimization and monitoring of teaching-learning processes, on the other hand, it raises deep cultural and pedagogical resistance within the academic community. The most deep-rooted concern in the scientific literature lies in the latent risk of a "dehumanization" of teaching, reducing complex educational dynamics to a mere cluster of quantifiable metrics (Selwyn, 2019; Williamson, 2017).

Evaluation, historically understood as a fundamental device of a communicative, relational, axiological, heuristic, and interpersonal nature between teacher and learner, risks being perceived as an alienating and aseptic process when it is entirely mediated by complex algorithms of massive computation. This tension touches the very heart of educational research, which claims methodological rigor alongside the unpredictability and subjectivity of the educational event in the face of algorithmic metrics.

This paper analyzes the complex transition from traditional to AI-assisted assessment models, focusing specifically on diagnostic assessment. Rather than presenting empirical investigations on actual teachers' attitudes, the paper establishes a theoretical-conceptual framework aimed at bridging technical data with pedagogical action. In contemporary university contexts—characterized by increasingly heterogeneous cohorts of students in terms of socio-cultural background and prior competencies—the timely diagnosis of cognitive prerequisites is essential to ensure equity, inclusion, and instructional effectiveness.

However, the transition to diagnostic AI must in no way constitute a technocratic drift or a weakening of the intellectual role and teaching freedom of the instructor; on the contrary, it represents an extraordinary opportunity for educational renewal, professional emancipation, and personalization of learning paths. The crucial core to determine the success of this transition lies in the strategic training of teaching staff and in the construction of a conscious "favorable disposition" toward these technologies. Far from assuming an uncritical acceptance, this contribution maps international evidence to highlight how a reflective posture—built through organic Faculty Development programs—acts as a vital catalyst, transforming statistical indicators into propulsive elements for inclusive instructional design (Farrokhnia, Brown, & Roberts, 2025).

2. Methodology

2.1 Research Design

From a methodological point of view, the present study adopts a systematic and critical literature review approach aimed at mapping the integration of Artificial Intelligence in higher education diagnostic assessment and structuring a theoretical-argumentative framework.

The literature search was conducted across major scientific databases (Scopus, Web of Science, ERIC) using specific Boolean strings intersecting 'Artificial Intelligence', 'Diagnostic Assessment', 'Higher Education', and 'Faculty Development'. The initial database query yielded a total of 264 contributions published in English between 2004 and 2026. Through a multi-step screening process, records were evaluated for contextual and methodological relevance:

- *Exclusions* **(**$n = 32$**):** A total of 32 contributions were excluded because they were exclusively theoretical opinion pieces

not focused on empirical or structured academic frameworks or lacked direct relevance to higher education faculty development.

- *Inclusions* **(**$n = 232$**):** The final corpus comprised the remaining 232 rigorously filtered studies, forming the basis for the thematic extraction, construct mapping, and the conceptualization of the algorithmic scaffolding model (Long et al., 2026).

The investigation adopts a heuristic design and a multi-perspective analysis paradigm. The exploration is articulated according to a design aimed at overcoming the dichotomy between technocentric approaches and technophobic resistances, proposing an original conceptual model of algorithmic scaffolding structured to support the reflective posture of the teacher. The procedure followed strict criteria for the selection of bibliographic sources (inclusion of empirical and theoretical studies focused on Higher Education in the period between 2004 and 2026), subsequently proceeding through five sequential macro-phases:

1. Analytical mapping of empirical evidence on the effectiveness of diagnostic assessment, Early Warning and academic drop-out prediction systems;
2. Comparative analysis of traditional evaluation models and identification of cultural barriers related to academic technophobia;
3. Conceptual infrastructure of the algorithmic scaffolding device, translating and declining the historical Vygotskian and Brunerian matrices within the information flows of Learning Management Systems (LMS);

4. Qualitative and ecological analysis of the proposed model, based on the intersection between the Technological Pedagogical Content Knowledge (TPACK) framework and the emerging instances of Explainable AI (XAI) applied to curricular early warning systems;

5. Ethical-docimological analysis of the implications related to computational reductionism, aimed at defining the guidelines for the training of university teachers (Faculty Development).

2.2. Variable Conceptualization and Categorization Framework

In order to ensure the reliability and operationalization of the study, the central phase of the methodology was focused on the conceptualization and systematic categorization of the variables extracted from the reference literature. The information and theoretical flows considered have been deconstructed and mapped according to three interconnected conceptual macro-categories:

- *Behavioral and Academic-Temporal Variables (Technical Input):* Categorization of digital tracking metrics extracted from Learning Management Systems (LMS), such as temporal latency and frequency of accesses, patterns of discursive interaction in forums and historical trends in training micro-assessments.
- *Psychopedagogical and attitude variables (Teacher Dimension):* Codification of the multidimensional construct of favorable disposition. This conceptualization isolated three key components of the university professor's posture: the cognitive dimension (algorithmic literacy), the affective dimension (management of technological anxiety and deconstruction of technophobia) and the design

dimension (inclusion-oriented Instructional Design) (Fartușnic, Istrate, & Fartușnic, 2025).

- *Scaffolding variables and Didactic Output (Systemic Dimension):* Categorization of the four operational phases that describe the human-machine pedagogical interface (Phase 1: Collection, Phase 2: Predictive Analysis, Phase 3: Cognitive Scaffolding, Phase 4: Relational Adaptation) and the Quality Assurance (QA) criteria required for the governance of academic data.

A rigorous conceptualization matrix made it possible to organize the theoretical model and to interpret the raw data of Learning Analytics not as isolated indicators, but as structural elements of an integrated training ecosystem. In order to provide an immediate visual synthesis of this conceptual architecture, the variables and their reference constructs have been mapped within the functional matrix presented in Table 1.

Table 1: *Conceptualization and categorization matrix of survey variables*

Macro-Category	Isolated Variables / Constructs	Example indicators / trackers	Pedagogical Output in the Model	Reference Source
Technical input *(behavioral variables)*	- Latency and access rate - Permanence on resources - Interaction in forums - Trend nei micro-assessment	- Moodle LMS Login Log - Monitoring of entrance test attempts - Download digital materials	Generation of automatic early warning alerts against drop-out	Siemens (2013); Conijn et al. (2017); Rastrollo-Guerrero et al. (2020); Pecuchova & Drlik (2024)
Teacher size *(Psychopedagogical variables)*	- *Favorable Disposition* - Algorithmic literacy - Managing Technological Anxiety	- Postura riflessiva del docente - De-costruzione della tecnofobia accademica	Transizione dell'IA da "agente minaccioso" a dispositivo di *scaffolding* didattico	Mishra & Koehler (2006); Chai et al. (2021); Ng et al. (2021); Farrokhnia et al. (2025); Fartușnic et al. (2025)
Systemic Size *(Scaffolding Variables)*	- Human-machine interface - Academic Data Governance - Quality Assurance (QA)	- 3D data cubes on active dashboard - Adaptive training modules - Collaborative classrooms in a circle	Alignment of the university educational offer with the real needs of students	Vygotskij (1978); Bruner (1983); Biesta (2015); Shibani et al. (2024); Knight & Buckingham Shum (2025); Talmoudi et al. (2025); Long et al. (2026)

Starting from this taxonomic framework, the process of document selection and subsequent extraction of data was articulated according to a procedural protocol divided into six sequential steps, aimed at ensuring transparency and replicability:

- *Step 1 – Database Query and Keyword Strategy:* The search was started on the main scientific databases (Scopus, Web of Science, ERIC) using Boolean search strings aimed at intersecting the macro-areas of the study (e.g., "Artificial Intelligence" AND "Diagnostic Assessment" AND "Higher Education" AND "Faculty Development").
- *Step 2 – Screening and Temporal Screening (2004–2026):* The records obtained were filtered by applying the criteria of

chronological and contextual inclusion, isolating contributions published between 2004 and 2026 structurally focused on higher education and academic staff training.

- *Step 3 – Quality and Impact Assessment:* The selected texts were subjected to a qualitative evaluation to verify their docimological and methodological adherence, excluding grey literature not subjected to peer review in order to ensure the scientific reliability of the diagnostic data considered.
- *Step 4 – Content Extraction and Thematic Analysis:* The analytical extraction of fundamental theoretical cores was carried out, isolating technical evidence on Learning Analytics and Early Warning systems alongside technological acceptance frameworks (TPACK, DigCompEdu).
- *Step 5 – Conceptualization and Theoretical Synthesis: The* extracted data were integrated into an original theoretical synthesis operating the pedagogical resignification of AI, conceptualizing the algorithm as a cognitive and affective scaffolding device for the instructor.
- *Step 6 – Categorization in Functional Matrix:* The integrated concepts were mapped within the four-phase operational model (Phase 1: Collection, Phase 2: Analysis, Phase 3: Teacher Scaffolding, Phase 4: Relational Adaptation in the classroom) constituting the backbone of the proposed intervention model.

2.3. Predictive Diagnostic Assessment and Combating Early School Leaving

Diagnostic assessment (Betts, Hahn, & Zau, 2011) is strategically placed in the early stages of the university experience or at the beginning of specific

curricular modules, with the explicit aim of mapping previous skills, unresolved conceptual knots, and potential cognitive barriers that could hinder students' learning (Brenner, 2022; Geiser & Santelices, 2007; Kaffenberger, 2021; Rylands & Coady, 2009; Shahzad & Ahmad, 2023).

In contemporary academic contexts, the effectiveness of this fundamental teaching practice has been limited by structural difficulties, notably the lack of formal pedagogical training among faculty (Cox & Richlin, 2004; Edgecombe et al., 2021; Tinto, 2012) in designing initial compensatory interventions for large student cohorts in a prompt manner. This limitation often compromises the overall effectiveness of instructional design and the possibility of timely curricular adjustments.

In this complex scenario, Learning Analytics (LA) systems and diagnostic AI hold the potential to intervene not as substitutes for human judgment, but as tools that expand the perceptive, interpretative, and decision-making capacities of the university professor (Siemens, 2013; Viberg et al., 2018). Subject to data quality and pedagogical supervision, the predictive processing of behavioral and academic patterns — such as student engagement metrics within Learning Management Systems (LMS), resource access rates, and intermediate self-assessment outcomes — can support instructional action on two crucial fronts:

- *Early identification of learning gaps:* Timely detection of specific conceptual deficiencies and cognitive bottlenecks before they become irreversibly consolidated throughout the academic trajectory (Betts, Hahn, & Zau, 2011; Shahzad & Ahmad, 2023);
- *Prevention of academic dropout:* Mitigation of early withdrawal risks through predictive algorithms that enable Early Warning Systems (Chung & Lee, 2019; Conijn et al., 2017; Rastrollo-Guerrero et al., 2020), facilitating the targeted activation of personalized mentoring and supplementary tutoring.

2.4. The Computation of Behavioral Patterns in Learning Management Systems (LMS)

The operational potential of an AI-enhanced diagnostic assessment rests on the technical infrastructure of Learning Analytics (LA). Within higher education digital environments, student interaction with online platforms (LMS) generates a continuous flow of digital traces. When critically processed and contextualized, these data points serve as an empirical foundation for ongoing predictive diagnostic mapping.

Rather than relying solely on the static results of initial standardized placement tests, machine learning models monitor behavioral and academic-temporal variables characterized by high informational density, including:

- The frequency, regularity, and temporal latency of access to learning materials uploaded by the instructor;
- The duration of interaction with specific digital resources and individual navigation pathways within course modules;
- The quantitative and qualitative patterns of interaction and peer collaboration within discussion forums and virtual learning spaces;
- Performance trends and score variations recorded across intermediate self-assessment activities and formative micro-evaluations.

The computational analysis of these behavioral patterns enables predictive algorithms to extend beyond a static evaluation of entry-level skills, assisting instructors in tracking the evolutionary dynamics of learning processes and identifying potential disengagement trends or cognitive difficulties in a timely manner (Hussain et al., 2018; Pecuchova & Drlik, 2024).

2.5 Mathematical-Predictive Mechanisms Against Academic Failure and Drop-Out

A significant horizon of these technologies lies in their capacity to generate predictive mathematical models aimed at counteracting academic failure and early university dropout (Nuzzaci, 2024). Through Machine Learning algorithms, the system compares real-time digital traces generated by current student cohorts with historical academic records stored on institutional servers from previous student trajectories. This computational process enables the early identification of specific behavioral variable combinations that have historically correlated with academic underperformance or progressive institutional disengagement.

Consequently, the system generates an Early Warning System that alerts instructors to statistically at-risk student profiles via an active dashboard. Crucially, as highlighted by docimological research, these algorithmic alerts do not possess deterministic value, nor do they represent a definitive labeling of the student. Rather, they function as subsidiary diagnostic indicators designed to inform faculty and academic tutors. This enables the timely activation of individualized support measures, targeted remediation pathways, and continuous academic guidance before cognitive gaps become irreversibly consolidated (Luckin, 2018).

However, the educational efficacy of these predictive mechanisms remains strictly conditional upon the quality and neutrality of historical datasets, the explainability of algorithmic metrics, and, above all, the critical interpretation of the university professor, who retains full pedagogical and docimological sovereignty over the instructional process.

Building upon the reviewed literature regarding Learning Analytics, Early Warning systems, and historical socio-cultural scaffolding matrices (Bruner,

1983; Vygotskij, 1978), the following section presents the authors' original conceptual contribution. To bridge technical data flows with intentional pedagogical action, an original four-phase conceptual model of algorithmic scaffolding is proposed, illustrating the theoretical procedure through which empirical literature evidence has been synthesized to support the instructor's reflective posture.

2. Results

Building upon the synthesized literature regarding Learning Analytics and historical scaffolding frameworks (Bruner, 1983; Vygotskij, 1978), the following section outlines the authors' original conceptual contribution: a four-phase algorithmic scaffolding model designed to support the reflective posture of the university teacher. This model bridges technical data flows with pedagogical action, ensuring that automated computational tools remain strictly subordinated to the instructor's professional judgment.

3.1. Empirical Evidence of Early Warning systems

The analytical mapping of the scientific literature highlights two primary strategic application fronts for diagnostic AI within higher education contexts. The first front concerns the early identification of learning gaps, which involves the timely detection of specific conceptual deficiencies and information gaps before they become irreversibly consolidated within the student's cognitive framework, thereby preventing cumulative learning deficits (Shahzad & Ahmad, 2023). In this manner, early diagnostic capabilities allow pedagogical interventions to precede formal academic failure. The second strategic front focuses on the prevention of academic drop-out through predictive analytics

that generate early warning alerts for students displaying a statistically high probability of course withdrawal (Luckin, 2018). Identifying initial learning bottlenecks enables the targeted and subsidiary activation of personalized mentoring, academic guidance, and supplementary instructional support. As documented in comprehensive literature reviews mapping AI algorithms in higher education (Rastrollo-Guerrero et al., 2020), predictive Early Warning Systems offer valuable opportunities to shift institutional logic from a reactive or bureaucratic paradigm—focused on evaluating failure post-hoc—to a preventive and support-oriented framework. This technical pipeline can be synthetically represented as follows:

$$\text{LMS Data (Moodle)} + \text{Career} \longrightarrow \underbrace{\text{Predictive Algorithm (Machine Learning)}}_{\text{Automatic processing on thousands of freshmen}}$$
$$\longrightarrow \text{Pre-Alarm Alert} \longrightarrow \text{Targeted compensatory tutoring}$$

However, as emphasized by docimological critical perspectives, Artificial Intelligence does not objectively or automatically replace teaching expertise or compensate for institutional constraints in an unconditional manner. Rather, under specific conditions—namely, high data quality, Explainable AI (XAI) standards, and ongoing professional interpretation—diagnostic algorithms can function as decision-support tools that make submerged learning needs visible across large student cohorts, directing personalized faculty action without overriding pedagogical autonomy.

3.2. Detailed Analysis of the Four Phases of the Algorithmic Scaffolding Model

The operationalization of the proposed algorithmic scaffolding model is articulated into four sequential and interconnected macro-phases, each

requiring specific reflective competencies on the part of the university instructor to prevent reductionist or technocratic drifts.

- *In Phase 1,* corresponding to diagnostic data collection, the digital learning environment generates interaction flows that, taken individually, constitute raw and neutral technical inputs. Through platform tracking within Learning Management Systems—including LMS logs, hourly access frequency, forum engagement, and entrance test performance—the system gathers data conveyed to institutional servers for secure storage. In this phase, faculty development aims to build awareness regarding data ecology, emphasizing that digital traces do not represent an absolute truth about the student, but clinical indicators requiring critical pedagogical interpretation.
- *Phase 2* constitutes the computational engine of the system, focused on predictive analysis and pattern identification. The accumulated raw data are processed through probabilistic algorithmic nodes, while the analytical interface translates data streams into trend metrics, matrices, and predictive curves. The output generated provides probabilistic statistical estimates, facilitating the early interception of conceptual gaps and the calculation of student drop-out risks.
- *In Phase 3,* the human-machine interface materializes through cognitive scaffolding for the teacher. At this stage, AI does not act directly or autonomously upon the student, but serves as a design-support architecture for the instructor. Displayed via active dashboards on PC or tablet devices through synthetic modular grids, this informational synthesis extends the teacher's perceptive capacities, enabling them to translate algorithmic alerts into structured

remediation plans, targeted mentoring, and adaptive delivery adjustments.

– *Finally, Phase 4* realizes the relational adaptation of learning, marking the essential return to the interpersonal and social dimensions of teaching. Macroscopic diagnostic data are transformed into intentional pedagogical action within a collaborative ecosystem. Guided by diagnostic insights, the instructor reorganizes classroom dynamics so that learning modules become adaptive, differentiated open resources are deployed, and physical or virtual classroom spaces are restructured to foster active, inclusive engagement, ultimately achieving precise alignment between instructional design and student needs.

4. Discussion

4.1. Beyond Technical Literacy: The Deconstruction of Institutional Technophobia

To structurally address the widespread perception of AI as a potential threat to the hermeneutical sensitivity, methodological freedom, and intellectual authority of the instructor, a systemic intervention on the professional culture of higher education faculty is essential. The professional development of university professors can no longer be configured as an ancillary or administrative task; rather, it represents a strategic priority to promote advanced digital literacy and mitigate institutional technophobia (Mishra & Koehler, 2006). The initial rejection of advanced algorithmic tools in academic contexts often stems not from intellectual resistance, but from a lack of integrated conceptual frameworks capable of connecting technological

capabilities with pedagogical principles. Consequently, Faculty Development programs must extend beyond technical-instrumental instruction or procedural software training, grafting technological competencies onto continuous pedagogical, ethical, axiological, and relational reflections (Chai et al., 2021). The fundamental objective of these professional development pathways is not the automation of instruction, but the conceptual reconfiguration of Artificial Intelligence itself. Within the instructor's professional experience, AI must be repositioned from an alienating or administrative burden to a cognitive, affective, metacognitive, and relational scaffolding device. This approach recontextualizes the foundational socio-cultural development and learning theories of Lev Vygotskij (1978) and Jerome Bruner (1983), applying them with heuristic rigor to contemporary digital learning environments. To provide a comprehensive synthesis of this professional development architecture, the core dimensions of algorithmic scaffolding within teacher training are summarized in Table 2, while the sequential workflow of the diagnostic process is illustrated in Figure 1.

Table 2: Dimensions of algorithmic scaffolding in teacher training

Type of Scaffolding	**Specified Teaching Function**	**Psychological and Professional Impact**
Cognitive Scaffolding	It supports superior mental functions and programming skills in the organization, synthesis and interpretative reading of large amounts of data (*Big Data*)	Translates computational complexity into clear didactic information, which can be used in the structuring of differentiated *remediation* paths for small groups or individual students
Affective Scaffolding	Unravel the inner workings and probabilistic logic of the algorithm through built-in digital literacy	It mitigates replacement anxiety and develops a strong sense of *self-efficacy*. It allows you to welcome technology as an ally for the educational success and well-being of the student
Metacognitive Scaffolding	It feeds the teacher's critical reflection on their teaching strategies, highlighting deviations between the planned objectives and real learning	Develops an aptitude for action-research and didactic flexibility. The teacher learns to consider the data not as a judgment, but as a resource for professional self-evaluation
Relational Scaffolding	It relieves the teacher of standardized and bureaucratic tracking, optimizing the time for educational mediation, pedagogical dialogue and qualitative feedback	Reconfigure the educator's identity from content provider to *mentor*. Strengthens the ethics of relational care and increases job satisfaction in interacting with students

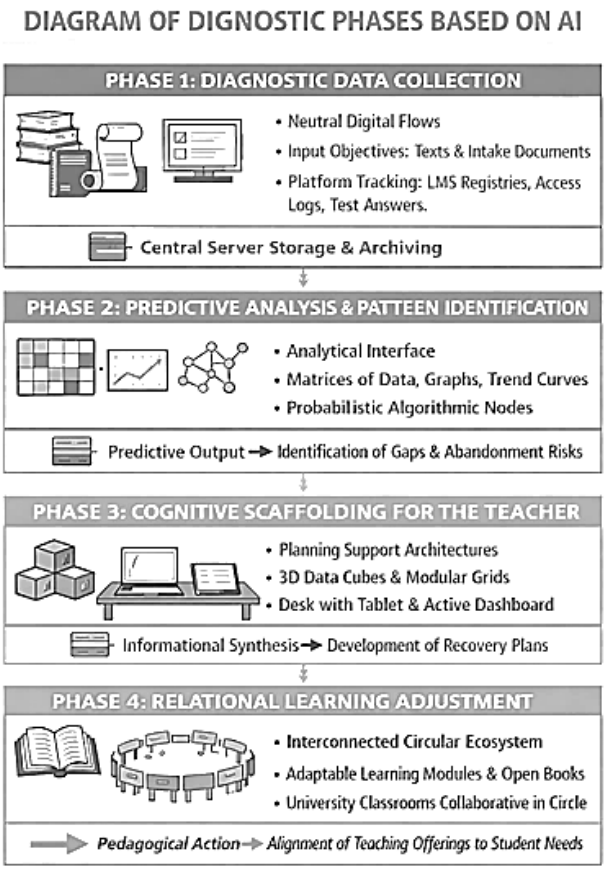


Figure 1: Diagram of diagnostic phases based on AI

4.2. The Construct of "Favorable Disposition": Operational and Epistemological Definitions

To fully understand the dynamics governing the integration of artificial intelligence systems into academic diagnostic assessment, it is necessary to deconstruct and analyze the construct of faculty "favorable disposition" at a theoretical level. In the international literature on Faculty Development, this concept is not reduced to a superficial satisfaction indicator or to a passive, uncritical acceptance of technological innovation. On the contrary, it is

configured as a complex, multidimensional, and intentional professional posture articulated along three fundamental dimensions: the cognitive dimension, concerning algorithmic literacy and the epistemological understanding of the tool; the affective dimension, involving the mitigation of technological anxiety and the deconstruction of perceived threats to intellectual autonomy; and the design dimension, reflecting the capacity to translate statistical indicators into inclusive pedagogical action.

The genesis of a favorable disposition is intrinsically linked to how university instructors perceive their professional role as cultural mediators, facilitators, and evaluators. If assessment is experienced merely as a bureaucratic or sanctioning act, the introduction of AI is inevitably perceived as further administrative automation. Conversely, when evaluation is understood in its original heuristic, diagnostic, and formative sense—as a device for detecting deeper learning needs and guiding educational success—the predictive algorithm ceases to be an alienating element. Instead, it becomes a strategic ally of the instructor's attentive gaze and a propulsive resource for human-machine pedagogical collaboration (Triberti et al., 2024).

4.3. The Intersection of Docimological Frameworks and AI Acceptance

The structuring of this positive attitude finds solid theoretical anchorage in established competence frameworks, such as Mishra and Koehler's (2006) TPACK model, its extensions to pedagogical AI knowledge (Chai et al., 2021), and related digital frameworks (Ng et al., 2021; Redecker, 2017). Extending these models to intelligent systems applied to diagnostic assessment requires that instructors do not simply possess isolated technological skills or disciplinary knowledge, but actively engage in a critical, reflective intersection among technology, pedagogy, and docimology (Zakarneh et al., 2025). AI-

assisted docimological training requires the development of an expanded form of professional knowledge (Di Tore et al., 2025). This focuses instructional design on pedagogical-algorithmic knowledge and on the critical capacity to govern the interaction between mathematical-predictive models and human learning processes. Designing instruction through this lens implies knowing how diagnostic algorithms process data, which variables exert the greatest weight on failure or drop-out risk calculations, and how this statistical evidence can be translated into differentiated teaching strategies within the classroom. Without this organic synthesis of technological competence and pedagogical reflection, the adoption of diagnostic AI risks failing, generating two opposing but equally harmful drifts: on the one hand, a priori rejection driven by institutional technophobia; on the other hand, a fideistic and uncritical acceptance of computational data. The latter deprives instructors of their intellectual and interpretative responsibility, hindering the development of genuine human-machine collaboration and critical pedagogical partnership (Shibani et al., 2024).

4.4. The Paradox of Automation: Reallocating Faculty Time to Pedagogical Care

A significant dimension highlighted in the literature lies in the potential of diagnostic automation and algorithmic computation to strengthen, rather than diminish, human and interpersonal pedagogical relationships. When university instructors are relieved of routine, highly repetitive tasks—such as manual test correction or the tracking of entry-level gaps across large student cohorts—they regain time and cognitive resources essential for exercising core instructional functions: intentional management of the educational relationship, active listening, and dialogic engagement (Biesta, 2015).

When conceptualized through this paradigm of intellectual subsidiarity, technological integration loses alienating connotations and serves as a supportive framework for faculty work. The time reallocated from quantitative data processing can be reinvested in the hermeneutic and relational dimensions of teaching, including individual academic advising, qualitative feedback, collaborative laboratory activities, and targeted student mentoring. In this model, computational tools address quantitative complexity, allowing faculty to focus on the qualitative, ethical, and interpersonal aspects of the pedagogical relationship.

4.5. Large-Scale Customization and Flexible Instructional Design

When supported by comprehensive Faculty Development initiatives, an instructor's reflective disposition facilitates the transformation of raw quantitative data into actionable pedagogical insight and flexible instructional design. Access to timely statistical indicators regarding entry-level student profiles—including baseline competencies, learning pace, and initial conceptual weaknesses—encourages faculty to move away from rigid, linear course designs.

Under these conditions, instructional design becomes an iterative and dynamic process. Instructors can adjust content delivery and pedagogical strategies in real time, calibrating lectures, seminars, and laboratory activities based on emerging learning needs identified through diagnostic analytics. This approach supports personalized learning pathways at scale—a goal historically difficult to achieve in higher education due to large class sizes. By enabling targeted instructional support without sacrificing collaborative and social classroom dynamics, diagnostic AI can assist faculty in distributing instructional attention more equitably across heterogeneous student cohorts.

4.6. Ethical Implications, Algorithmic Reductionism, and the Protection of Equity

While the integration of diagnostic AI offers valuable opportunities for personalizing instruction at scale, learning analytics must critically address the ethical and docimological implications associated with automated systems. A primary concern highlighted in critical educational literature is algorithmic reductionism—the tendency to simplify the complexity of human learning, educational biographies, and individual potential into standardized quantitative metrics (Williamson, 2017).

When applied without pedagogical supervision, predictive models risk incorporating and reinforcing existing systemic biases, potentially exacerbating initial educational inequalities rather than mitigating them. For instance, an algorithm profiling a student as "at high risk of dropout" based solely on historical statistical correlations (Nuzzaci, 2024) could inadvertently induce a Pygmalion effect or self-fulfilling prophecy. This risk can negatively influence faculty expectations and student self-efficacy, particularly for underrepresented groups or students experiencing persistent digital infrastructure gaps (Cullinan et al., 2021). Consequently, educational equity and inclusion require that algorithmic outputs remain continuously subordinated to the critical judgment of the instructor, who must interpret statistical indicators not as definitive outcomes, but as diagnostic starting points to inform supportive interventions.

To mitigate these risks, Early Warning Systems must rely on high ecological and methodological data quality. Supplying predictive models with contextualized, accurate data free of discriminatory bias represents an essential ethical and pedagogical imperative. Ultimately, Artificial Intelligence holds the potential to

support teaching and assist in preventing academic withdrawal, provided that strict data quality is maintained, algorithms remain transparent and explainable (XAI), and instructors exercise ongoing professional interpretation rather than relying on deterministic metrics. Rigorous pedagogical oversight across the data processing pipeline ensures that algorithmic tools function as instruments for educational support and student empowerment rather than bureaucratic labeling devices.

4.7. For a Transparent Algorithm Pedagogy: Explainable AI (XAI) in Evaluation

To safeguard the democratic, ethical, and transparent nature of higher education, it is essential to promote the transition from algorithmic "black box" systems—opaque computational models whose internal calculation mechanisms remain inaccessible to faculty—to frameworks inspired by Explainable Artificial Intelligence (XAI). University instructors must be placed in a position to understand the underlying logic guiding machine outputs, identifying which specific indicators generated a diagnostic alert and what weight was attributed to individual analytical dimensions (Talmoudi et al., 2025).

Docimological transparency represents a fundamental principle for both instructors and students: it ensures full intellectual sovereignty and responsibility for the evaluator while protecting the learner’s academic career from unscrutinized or inscrutable computational decisions. Students must never perceive their educational progression as heterodirected by an aseptic algorithmic entity. Ultimately, only through a conscious alliance and critical dialogue between the human pedagogical intelligence of the teacher and the computational capacity of the algorithm will higher education institutions be

able to combine the scientific efficiency of data analytics with the ethics of responsibility and relational care.

5. The Strategic Horizon of Academic Governance in the Age of Global AI

The structural integration of AI in diagnostic and predictive assessment is not simply a technical-methodological transition; it requires a radical reconfiguration of university policies and strategic academic governance on a national and international scale (Crompton & Burke, 2023). Examining long-term scenarios highlights an urgent need for higher education institutions to move beyond fragmented and impromptu adoptions of digital tools toward organic regulatory frameworks. In this context, universities cannot limit themselves to being passive consumers of proprietary commercial technologies—often governed by opaque, profit-oriented logics that risk commodifying student data streams (Williamson, 2017). On the contrary, ethical and scientific oversight of the diagnostic data pipeline must be structurally integrated into institutional quality assurance policies.

In the domains of Quality Assurance (QA) and educational innovation, the effectiveness of instructional processes and the prevention of early drop-out must become strategic objectives of university monitoring systems. From this perspective, the pedagogical validation of predictive algorithms and the docimological transparency of Early Warning Systems represent critical institutional requirements. Only academic governance that embeds data ethics and protection into its self-assessment and continuous improvement processes can ensure that AI adoption respects equity, sustainability, and student-centricity, promoting genuine technological sovereignty in line with regulatory developments.

Consequently, future university policies must allocate systemic and infrastructural investments to develop transparent, flexible Learning Analytics platforms based on open-source paradigms, ensuring central servers remain under public and academic oversight. This institutional strategy is essential to protect student privacy and guarantee that predictive algorithms remain free from discriminatory biases based on gender, ethnicity, or socio-economic status. The favorable disposition of faculty cannot develop in a regulatory vacuum; it must be sustained by university policies that explicitly subordinate algorithmic code to the pedagogical autonomy and academic freedom of teaching staff.

6. Towards an Adaptive Curricular Design: The Metamorphosis of the Educational Offer

On an instructional level, the availability of AI systems capable of performing continuous and accurate predictive diagnoses of prerequisites and cognitive needs forces a fundamental rethinking of university curricular architecture (Siemens, 2013; Viberg et al., 2020). Traditional educational offerings—historically rigid, linear, and standardized regardless of starting backgrounds—appear increasingly inadequate for the complexity of contemporary student cohorts. Long-term scenarios point to the emergence of fluid and adaptive curricula, wherein macro-level course design merges with micro-level personalization enabled by diagnostic tools.

Through the early detection of learning gaps and engagement patterns, course design can dynamically remodulate. Standard instructional modules are accompanied by targeted alignment and enhancement pathways activated on a subsidiary basis; content delivery adapts to the assimilation pace of both the cohort and individual learners through dedicated remediation or enrichment

hubs; and assessment is no longer confined to end-of-term summatives, but distributed throughout the learning trajectory to provide continuous qualitative feedback to students and instructors alike (Biesta, 2015).

Far from isolating students behind screens, an AI-mediated adaptive curriculum recreates conditions for advanced community-oriented instruction. Informed by diagnostic profiles, instructors can organize collaborative learning, peer tutoring, and targeted workshops, grouping students based on emerging cognitive affinities or complementarities rather than random assignment. This approach operationalizes and fulfills long-standing theoretical frameworks of instructional individualization (Bloom, 1968, 1976; Gagné, 1965; Keller, 1968).

7. Conclusions

Rather than presenting empirical validations of teachers' actual attitudes or a tested measurement of behavioral change, this contribution outlines a conceptual framework, offering methodological reflections and working hypotheses for future Faculty Development programs aimed at supporting university teaching in the age of AI.

In this complex transition framework, Faculty Development and continuous pedagogical training programs for university professors cease to be optional, standing as an essential pillar for the sustainability of the higher education system (Knight & Buckingham Shum, 2025; Mishra & Koehler, 2006). The future challenge requires preparing academic professionals who possess technological wisdom and a solid ethical posture, capable of exercising constant critical vigilance against computational reductionism (Selwyn, 2019).

The university of tomorrow is called to reconcile the analytical efficiency and statistical accuracy enabled by large-scale data processing with the ethics of relational care, clinical listening, and cultural emancipation (Biesta, 2015).

Preserving this essential alliance among computational capacity, human intelligence, and pedagogical intentionality remains the sole guarantee that technological innovation will yield genuine democratic progress, guiding each student toward full educational and existential success.

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