

Article

A Conceptual Model of Hybrid Intelligent Assessment Systems for Higher Education

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Abstract

Rapidly expanding use of Generative Artificial Intelligence (GenAI) in higher education creates both opportunities and challenges for learning assessment. While GenAI can provide adaptive feedback and personalization, its pedagogical integration remains underdeveloped and often disconnected from established theories of learning and participatory design processes. This paper addresses this gap by proposing an integrative conceptual model of Hybrid Intelligent Assessment Systems (HIAS), which combines AI capabilities with human oversight to enable transparent, ethical, and pedagogically aligned assessment. HIAS is structured through three interdependent layers of adoption: a pedagogical layer, aligning AI-supported assessment with self-regulated learning and the development of knowledge, skills, and attitudes; a governance layer, ensuring transparency, fairness, and human-in-the-loop validation; and a technological layer, enabling scalable integration within digital learning environments. The study is situated in Estonia, a digitally advanced context with system-level AI integration through the national AI Leap initiative. To complement the conceptual model, an empirical study was conducted across three major Estonian universities, involving 66 professors and researchers and 153 students. In addition, a small-scale pilot implementation was conducted in a design thinking course to explore the practical feasibility of a course-specific HIAS-based AI assistant. The findings reveal a consistent pattern: while both groups demonstrate a broadly positive orientation toward AI, students approach AI primarily as an efficiency-driven learning tool, whereas academic staff emphasize pedagogical control, ethical considerations, and responsible use. Across both groups, AI literacy remains uneven, particularly in critical evaluation and structured application. These findings expose a critical gap between rapid AI adoption and insufficient pedagogical integration. In response, HIAS is proposed as a structured, human-centered framework that supports teachers in designing AI-enhanced learning environments and students in developing critical, self-regulated, and responsible use of AI.

Keywords: Hybrid Intelligent Assessment Systems; generative artificial intelligence; self-regulated learning; AI literacy; EdTech

Academic Editor: Mike Joy

Received: 1 May 2026

Revised: 17 June 2026

Accepted: 9 July 2026

Published: 10 July 2026

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1. Introduction

Education is an essential driver of global development and is closely aligned with the Sustainable Development Goals (Ferrer-Estévez & Chalmeta, 2021). Over time, it has transformed from traditional classroom-based instruction into increasingly digital and flexible learning environments shaped by successive industrial revolutions (Giovannella, 2024; Rakic et al., 2021). This transformation accelerated during the COVID-19 pandemic, when lockdowns exposed the limitations of classical education systems and forced a rapid transition to online learning (Alejo et al., 2024). Today, higher education faces new pressures caused by the large-scale adoption of digital technologies, particularly artificial intelligence (AI) and Generative Artificial Intelligence (GenAI) (Lundin et al., 2023).

GenAI, especially large language models, is reshaping learning, teaching, and assessment. These technologies enable students and teachers to access, generate, and process information in new ways, while also raising important pedagogical and ethical concerns (Leoste et al., 2025). GenAI systems have demonstrated strong performance in several domains, creating high expectations for their use in personalized tutoring, formative feedback, and assessment (Liao et al., 2024). However, their integration into higher education remains uneven and insufficiently regulated. AI tools are increasingly used in classrooms and assessment workflows without adequate pedagogical grounding, governance frameworks, or participatory design processes (Jin et al., 2025). Despite rapid technological progress, higher education still lacks an integrated conceptual framework that systematically connects AI-enabled assessment with learning theory, governance requirements, participatory design, and AI literacy development.

European policy frameworks have started to address these risks. The EU Artificial Intelligence Act classifies educational AI systems used in learning assessment as “high-risk” because of their implications for fairness, transparency, and privacy (European Commission, 2024). Higher education institutions must therefore respond not only by adopting AI tools, but also by ensuring their responsible, pedagogically meaningful, and controlled use (Banihashem et al., 2025).

One promising response is to position self-regulated learning (SRL) as a pedagogical foundation for AI-supported assessment. SRL enables students to plan, monitor, and reflect on their learning while maintaining learner agency and teacher support (Chiu, 2024). Conceptualized in models such as Zimmerman’s three-phase cycle of forethought, performance, and reflection (Zimmerman, 2002) and Winne and Hadwin’s four-phase model (Banihashem et al., 2025), SRL is widely recognized as a foundation for academic success and lifelong learning. However, AI use also raises new assessment-related concerns, as students increasingly rely on AI for problem-solving, essay writing, coding, and other academic tasks (Lundin et al., 2023). A key challenge is therefore to design AI assistants that support students across the learning cycle while ensuring that assessment remains valid, ethical, and human-supervised (Nitu et al., 2024).

Recent research shows that many students still struggle to monitor and regulate their own learning (Ng et al., 2024). AI-supported technologies, including intelligent tutoring systems such as MetaTutor and more recent chatbot-based tools, can scaffold SRL by prompting planning, monitoring, and reflection (Molenaar et al., 2023). This makes SRL a strong pedagogical foundation for integrating AI into assessment in ways that support learner agency rather than replace it (Jin et al., 2025). Nevertheless, current AI use in higher education remains fragmented. Many AI-enabled assessment tools operate as “black boxes,” generating automated scores or feedback without sufficient transparency, teacher oversight, or theoretical grounding (Nikolic et al., 2023). Others are domain-specific, monolingual, or limited to particular assessment formats (Liao et al., 2024). This fragmentation highlights the need for a hybrid assessment architecture that integrates pedagogical theory, governance safeguards, technological transparency, participatory co-

design, and AI literacy development within a single coherent model. Participatory Design (PD) offers a promising but still underdeveloped approach for integrating AI into higher education assessment. PD emphasizes mutual learning, negotiation of values, and shared decision-making among stakeholders (Giovannella, 2024). In the HIAS model, PD functions as a cross-cutting design principle rather than as a separate layer. While SRL provides the pedagogical foundation for supporting students' planning, monitoring, and reflection, and the SOLO taxonomy supports the structuring of learning progression, PD explains how AI-supported assessment can be co-shaped by teachers, students, and institutional stakeholders. For students, using an AI assistant becomes part of a human-computer interaction process in which they actively co-design their learning work with AI by asking questions, testing ideas, revising project outputs, reflecting on feedback, and deciding how to integrate AI-generated suggestions into their own learning process. For teachers, PD supports the definition of course-specific materials, assessment criteria, feedback matrices, feedback boundaries, and human oversight mechanisms. Therefore, PD strengthens HIAS by connecting transparency, stakeholder involvement, contextual alignment, and responsible AI use with the pedagogical goal of supporting self-regulated learning. Based on this, the research question guiding this paper is:

RQ: How can hybrid intelligent assessment methods, integrated with self-regulated learning, support the ethical adoption of GenAI in higher education?

Building on SRL, PD, and responsible AI governance, this paper introduces the HIAS model as a conceptual framework for AI-supported assessment in higher education. HIAS integrates three interdependent layers:

Pedagogical: aligning GenAI with SRL and the assessment of Knowledge, Skills, and Attitudes (K-S-A).

Governance: embedding transparency, human-in-the-loop oversight, and ethical safeguards in accordance with the EU AI Act.

Technological: defining complementary roles for AI and teachers, while enabling multilingual and modular integration into learning management systems.

This study also proposes an AI literacy evaluation framework aligned with the updated descriptors of DigComp 3.0. The framework extends existing competence models by incorporating dimensions related to the responsible, ethical, and innovative use of GenAI. By integrating AI literacy progression with hybrid assessment design, it offers a structured pathway for implementing ethical, inclusive, and participatory assessment practices in higher education.

The study is situated in Estonia, a digitally advanced context that has launched the national AI Leap initiative to support the systematic integration of AI into education. This context provides a strategic reference point for examining university readiness for AI-supported teaching and assessment. The empirical readiness analysis of university staff and students informed the development of a context-sensitive HIAS model capable of supporting the structured, ethical, and pedagogically grounded introduction of AI-driven hybrid assessment.

The remainder of this paper is structured as follows. Section 2 outlines the theoretical foundations of the model, drawing on SRL theory, AI in education, and assessment methods. Section 3 presents the methodology, including the sample, data collection, and data analysis procedures. Section 4 presents the AI literacy survey results and the HIAS model. Section 5 discusses the theoretical and practical implications. Section 6 concludes with limitations and future research directions.

2. Theoretical Background

2.1. Self-Regulated Learning

SRL is a central construct in learning sciences, describing how learners actively manage their cognition, motivation, and behaviour to achieve academic goals (Zimmerman, 2002). SRL emphasizes learner agency by positioning students not as passive recipients of instruction, but as active participants who plan, monitor, and reflect on their learning (Kong & Yang, 2024). Two major frameworks are particularly influential in SRL research: Zimmerman's three-phase model of forethought, performance, and reflection, and Winne and Hadwin's four-phase model, which includes task definition, goal setting and planning, enactment, and adaptation (Molenaar et al., 2023). Both models describe SRL as a recursive process in which learners continuously adjust their strategies based on feedback and outcomes.

Research has established SRL as an important predictor of academic achievement across disciplines and educational levels (Banihashem et al., 2025). However, supporting SRL in educational practice remains challenging, as many students lack the metacognitive awareness or motivational strategies needed to self-regulate effectively (Ng et al., 2024). Interventions such as reflective journals, prompts, and peer feedback can improve SRL, but they often require sustained teacher involvement, which may not be scalable in large or diverse classrooms (Molenaar et al., 2023).

Technology-enhanced learning environments have attempted to address this challenge by embedding SRL scaffolds into digital platforms. Intelligent tutoring systems (ITS), such as MetaTutor, use pedagogical agents and adaptive prompts to guide learners through SRL processes, supporting goal setting, progress monitoring, and reflection (Lan & Zhou, 2025). Empirical findings suggest that such scaffolds can improve metacognitive awareness and learning outcomes. However, these systems often rely on predefined strategies, have limited flexibility in responding to diverse learner needs, and may struggle to address affective and motivational dimensions of learning (Chang et al., 2023).

GenAI introduces new possibilities for SRL support. Unlike traditional ITS, GenAI can generate context-sensitive and adaptive feedback in real time, enabling dynamic scaffolding of cognitive, motivational, and emotional dimensions of SRL (Ng et al., 2024). For example, AI-powered chatbots can simulate tutoring dialogues that encourage reflection, provide feedback aligned with rubric criteria, and suggest alternative learning strategies (Weng et al., 2024). At the same time, uncritical AI use may create dependency, whereby learners outsource self-regulation to machines rather than developing their own strategies (Strait et al., 2020).

Thus, SRL provides a robust pedagogical foundation for hybrid intelligent assessment. By aligning AI feedback with SRL processes of forethought, performance, and reflection, educators can ensure that AI tools scaffold rather than replace learner agency (Wang & Lin, 2023). The challenge is to design hybrid systems that use AI to augment human teaching while maintaining transparency, fairness, and learner autonomy.

2.2. Artificial Intelligence in Education

AI has a long history in education, beginning with early rule-based tutoring systems in the 1970s and evolving into adaptive learning environments that respond to student input (Castillo-Martínez et al., 2024). The advent of large language models (LLMs) marks a transformative shift, as GenAI can now simulate natural conversation, generate domain-specific feedback, and adapt explanations to learners' needs in ways that earlier systems could not (Crompton & Burke, 2023). Recent research highlights both the potential and the risks of AI in education (Bearman et al., 2023). On the positive side, AI can provide personalized feedback at scale, detect learner misconceptions, and generate adaptive

learning tasks (Liao et al., 2024). For instance, AI-enabled visual report tools can enhance formative feedback by presenting learners with individualized progress dashboards (Nikolic et al., 2023). Similarly, AI-driven writing assistants can support academic writing by suggesting revisions and identifying gaps (Neumann et al., 2023).

However, the educational use of AI remains fragmented and often lacks theoretical grounding (Mienye & Swart, 2025). Many applications focus narrowly on automating repetitive tasks, such as essay scoring or quiz generation, without embedding these tools into broader pedagogical frameworks (Nikolic et al., 2023). The risks of such approaches are significant: opaque algorithms may reproduce bias, undermine fairness, and erode trust in assessment (Michel-Villarreal et al., 2023). Moreover, students and teachers often remain uncertain about the role AI plays in assessment processes, raising concerns about transparency and accountability (Bearman et al., 2023).

European policy frameworks explicitly recognize these challenges. The EU Artificial Intelligence Act classifies AI systems used in educational assessment as high-risk, requiring transparency, explainability, and human oversight in contexts where automated decision-making may affect learners' opportunities and outcomes (European Commission, 2024). Similarly, the DigComp 3.0 framework emphasizes AI literacy as a key competence for both learners and educators, highlighting the need to use AI responsibly and critically. Scholars increasingly argue for hybrid approaches to AI in education, where GenAI provides adaptive and data-driven support, while teachers ensure contextual interpretation, ethical judgment, and human care (Banihashem et al., 2025). Participatory design perspectives further stress the need to involve educators and learners in shaping how AI is used, ensuring that AI systems align with educational values, disciplinary needs, and cultural contexts (Van Den Broek et al., 2024). In this context, HIAS emerges as a response to both the promise and risks of AI in education. It aims to combine the efficiency and adaptability of GenAI with human oversight, transparency, and participatory governance, ensuring that AI contributes to educational integrity rather than undermining it.

2.3. Assessment Methods

Assessment is one of the cornerstones of higher education, shaping not only learning outcomes but also students' approaches to learning (Pereira et al., 2016). Traditional summative assessment methods, such as final exams or standardized tests, remain dominant, yet they primarily capture learning outcomes rather than learning processes (Flores et al., 2015). In contrast, formative assessment provides feedback during learning, enabling students to reflect, adjust strategies, and improve performance (Morris et al., 2021). Research consistently shows that formative assessment supports deeper learning and self-regulated learning (SRL) more effectively than summative assessment alone (Sillat et al., 2021). Self-assessment and peer assessment have also gained attention because they engage learners directly in evaluation and foster responsibility, critical thinking, and metacognition (Ng et al., 2024). These practices align with participatory design principles by positioning students as co-agents in the assessment process. However, challenges remain, as students may lack confidence in evaluating peers, cultural norms can shape participation, and bias may affect fairness (Flores et al., 2015).

Frameworks such as the SOLO taxonomy provide structured ways to classify learning outcomes, ranging from surface understanding, including unistructural and multistructural responses, to deeper understanding, including relational and extended abstract responses (Svensäter & Rohlin, 2023). This taxonomy helps educators align assessment tasks with cognitive complexity and provides a roadmap for scaffolding learner progression. Similarly, the Level 5 framework has been used to structure competence development across knowledge, skills, and attitudes at ascending levels of

mastery (Scholze, 2025). When integrated with AI-supported assessment, these frameworks can help move assessment beyond product evaluation toward process-oriented scaffolding (Sillat et al., 2021).

AI has already been integrated into assessment in several ways, including automated grading of multiple-choice items, AI-driven essay scoring, plagiarism detection, and adaptive testing (Nikolic et al., 2023). While these tools increase efficiency, they also risk narrowing assessment to easily quantifiable outcomes (Sokhanvar et al., 2021). More recent approaches have used AI for formative purposes, such as generating adaptive quizzes, analysing student reflections, and visualizing learning analytics dashboards (Liao et al., 2024). Yet many of these applications remain isolated and often lack scalability, inclusivity, or governance safeguards (Memarian & Doleck, 2023). For higher education to fully benefit from AI, assessment must evolve toward Hybrid Intelligent Assessment Systems (HIAS) that integrate formative, summative, self-, and peer-assessment while embedding transparency, fairness, and ethical oversight. Such systems should support learners' SRL, promote AI literacy, and respect participatory design principles, ensuring that AI acts as a scaffold for learning rather than as a substitute for human judgment.

3. Methodology

This study adopts a conceptual–empirical research design, combining theoretical model development with empirical investigation to inform the design and implementation of Hybrid Intelligent Assessment Systems (HIAS) in higher education. The methodological approach integrates a literature-based conceptual foundation with contextual empirical analysis aimed at assessing the readiness of academic staff and students to adopt and use generative artificial intelligence (GenAI) in educational settings.

Estonia was selected as the study context because of its strong position in digital education and innovation. The country consistently ranks among the top-performing European education systems in international assessments such as the Programme for International Student Assessment (PISA), reflecting a highly adaptive and future-oriented education system. In addition, Estonia has recently launched national initiatives such as AI Leap, which aims to integrate artificial intelligence into secondary education and better prepare students for higher education and the evolving labour market. These developments make Estonia a relevant context for examining AI integration across educational levels.

Building on this context, the study assesses the readiness of university staff and bachelor-level students in terms of their knowledge, skills, and attitudes toward AI. The objective is to identify key gaps and development needs that can inform the design of a structured, pedagogically grounded, and ethically aligned HIAS model.

Data collection was conducted between January 2026 and March 2026, during a period of active institutional engagement with AI-supported teaching and learning practices. Academic staff participated during organized AI training sessions within universities, while students contributed voluntarily during lectures in courses supported by AI assistants. These implementations were not experimental prototypes, but part of an ongoing institutional initiative.

Following the development of the HIAS conceptual model, a small-scale pilot implementation was conducted to examine how the model could be operationalized in a real higher education course. The pilot was carried out during the spring semester of 2026 in a 15-week elective course on design thinking at one Estonian university. The course was selected because its project-based and challenge-based structure required continuous formative feedback, weekly task clarification, student reflection, and iterative project development. Six students from different academic backgrounds participated in the pilot evaluation. For the implementation, students were provided with access to the paid

ChatGPT Edu (GPT-5) environment, enabling them to use a course-specific AI assistant developed according to HIAS principles. The assistant was configured with curated course materials, weekly instructions, assignment descriptions, and professor-defined guidance. During the semester, students completed more than 100 interaction iterations with the course assistant, using it to clarify tasks, understand course content, prepare deliverables, and receive formative support.

The pilot evaluation followed a mixed-methods approach. Quantitative data were collected through a structured questionnaire based on a five-point Likert scale, measuring students' perceptions of the assistant's pedagogical usefulness, feedback and pre-assessment support, governance and human oversight, trustworthiness, and comparison with general-purpose AI tools. Qualitative data were collected through open-ended questions designed to capture students' experiences, perceived benefits, limitations, and suggestions for further improvement. Given the small number of participants, the pilot was not intended to provide statistical validation of the HIAS model. Instead, it served as an exploratory evaluation of practical feasibility and as an illustrative case of how HIAS can be embedded into a course-level learning and assessment process.

3.1. Data Collection

Data were collected using a structured survey instrument designed to assess AI literacy and readiness among academic staff and students. Participation was voluntary, and respondents were informed about the purpose of the study. The instrument was based on an adaptation of the DigComp 3.0 and OECD competence frameworks and was extended to capture AI-specific competencies. AI literacy was operationalized across three dimensions: knowledge, referring to understanding of AI concepts and systems; skills, referring to the ability to use AI tools in practical contexts; and attitudes, referring to perceptions, critical awareness, and ethical orientation toward AI. To structure the assessment, a five-level progression model aligned with the HIAS framework was defined, ranging from basic awareness to advanced expertise. Participants were asked to self-assess their level across these dimensions using items adapted to their role as either academic staff or students. Table 1 presents the AI Literacy Evaluation Framework.

Table 1. AI Literacy Evaluation Framework.

HIAS Level	Knowledge (What Student Knows About AI)	Skills (What Student Can Do with AI)	Attitudes (How Student Relates to AI)
1—Awareness (Basic)	Recognises AI in daily tools (search engines, chatbots).	Uses AI for simple Q&A tasks with guidance.	Curious about AI but passive; open to trying.
2—Basic Application (Basic/Intermediate)	Understands basic AI concepts (ML, GenAI, algorithms).	Applies AI for routine tasks (summaries, translations).	Accepts AI guidance cautiously; recognises presence of AI in tools.
3—Independent Application (Intermediate)	Explains how AI systems generate outputs (training data, patterns, biases).	Uses AI for academic tasks (drafting, coding, analysis) with some independence.	Reflects critically on limits/risks of AI in own learning.
4—Transfer/Integration (Advanced)	Evaluates credibility & reliability of AI	Adapts AI use to different tasks (research,	Values responsible use; collaborates

	outputs across contexts.	teamwork, presentations).	ethically with peers using AI.
5—Innovation/Expertise (Highly Advanced)	Keeps up-to-date with new AI trends and societal implications.	Designs AI workflows/prompt s; creates innovative solutions using AI tools.	Advocates for ethical, fair, and transparent AI use; inspires peers and leads discussions.

In addition, the survey included open-ended questions designed to capture deeper insights into participants' understanding of AI, their current capabilities, perceived challenges, and purposes for using AI in learning contexts. To assess internal consistency, Cronbach's alpha was calculated for both the student and staff versions of the instrument. Both versions included 15 Likert-scale items organized across three AI literacy dimensions: knowledge, skills, and attitudes, with five items per dimension. The student instrument demonstrated good overall reliability ($\alpha = 0.887$), with acceptable to good reliability across the knowledge ($\alpha = 0.851$), skills ($\alpha = 0.807$), and attitudes ($\alpha = 0.796$) subscales. The staff instrument also demonstrated good overall reliability ($\alpha = 0.835$), with good reliability for knowledge ($\alpha = 0.858$) and skills ($\alpha = 0.839$). The staff attitudes subscale showed lower internal consistency ($\alpha = 0.627$), suggesting that staff attitudes toward AI may represent a more heterogeneous construct involving curiosity, ethical caution, transparency, and advocacy for responsible AI use. Given the exploratory purpose of the study, the reliability results were considered sufficient for identifying general readiness patterns, while the staff attitudes subscale was interpreted with caution.

3.2. Sample

The study involved two participant groups: academic and professional staff, and students. In total, 66 academic and professional staff members and 153 bachelor-level students participated in the study between January 2026 and March 2026. Tables 2 and 3 show the demographic characteristics of the sample.

Table 2. Demographic characteristics of university staff.

Category	Sub-Category	N	%
Gender	Female	37	56.1
	Male	28	42.4
	Prefer not to say	1	1.5
Position	Early-Stage Researcher	25	37.9
	Lecturer	18	27.3
	Management Staff	11	16.7
	Researcher	7	10.6
	Professor	5	7.6
Age Range	20–29	13	19.7
	30–39	21	31.8
	40–49	24	36.4
	50–59	7	10.6
	60+	1	1.5

The academic and professional staff sample represented a diverse group across different career stages, with a predominance of early-stage researchers and lecturers. The age distribution indicated a largely mid-career population. Participants came from a wide range of disciplines, including artificial intelligence, engineering, life sciences, business,

and education. All staff participants were based in Estonia, ensuring consistency with the national context of the study.

Table 3. Demographic characteristics of student participants.

Category	Sub-Category	N	%
Gender	Male	109	71.2
	Female	33	21.6
	Prefer not to say	10	6.5
	Non-binary	1	0.7
Age Range	18–20	75	49.0
	21–23	54	35.3
	24–26	13	8.5
	27–29	4	2.6
	30+	7	4.6
Field of Study	IT/Software/Systems Development	74	48.4
	Cybersecurity	67	43.8
	Other	12	7.8
Nationality	Estonia	127	83.0
	International	26	17.0

The student sample consisted exclusively of undergraduate students enrolled in technology-oriented programmes. Most participants were in the early stages of their studies, particularly within the 18–23 age range. The sample was strongly oriented toward IT and cybersecurity disciplines, reflecting the institutional profile. Although all students were enrolled in Estonian higher education institutions, 17% were international students, contributing to the diversity of perspectives.

3.3. Data Analysis and Conceptual Model Development

The data were analyzed using descriptive statistical analysis and qualitative thematic analysis. Descriptive statistics were used to examine the distribution of participants across different AI literacy levels, based on their self-assessment of knowledge, skills, and attitudes. Because the instrument relied on self-reported data, the results are interpreted as indicators of perceived AI literacy readiness rather than as direct measures of actual AI competence. This approach was appropriate because the aim of the study was not to test technical performance, but to identify readiness patterns, perceived development needs, and stakeholder orientations toward the pedagogical and ethical use of GenAI in higher education. These perceptions were important for informing the conceptual development of HIAS, as successful implementation of AI-supported assessment depends not only on technical skills, but also on users' confidence, perceived needs, ethical awareness, and willingness to engage with AI-supported learning and assessment practices. The quantitative analysis therefore enabled the identification of general readiness patterns among academic staff and students. Qualitative responses were analyzed thematically to identify recurring patterns related to challenges, learning needs, and AI usage practices, providing additional depth and context to the quantitative findings.

The development of the HIAS conceptual model was based on the integration of theoretical foundations, policy frameworks, and empirical findings from the study. The readiness analysis enabled the identification of key gaps between current AI adoption practices and pedagogically grounded, ethically aligned use. These insights informed the structuring of the HIAS model into three interdependent layers: pedagogical, governance, and technological. Furthermore, the ongoing implementation of AI-supported learning environments across multiple courses at an Estonian university provided a practical

context for refining the conceptual model and exploring its feasibility in authentic teaching and learning settings.

4. Results

4.1. AI Literacy Readiness of University Staff

The AI literacy readiness of both university staff and students was assessed using a five-point Likert scale (1–5), where respondents self-evaluated their level of agreement with statements corresponding to five progressive levels of competence across three dimensions: knowledge, skills, and attitudes. The scale reflects increasing levels of AI literacy, ranging from basic awareness to advanced expertise. Higher mean values indicate stronger perceived readiness to operate at a given competence level.

To enable clearer comparison between the two respondent groups and across the three AI literacy dimensions, the mean scores were converted into normalized percentage values. These values do not represent the percentage of respondents selecting a specific response option. Instead, they represent the mean score for each dimension and competence level expressed as a percentage of the maximum possible score on the five-point scale. For example, a value of 80% corresponds to an average score of 4.0 out of 5.

Therefore, the values reported in Tables 4 and 5 should be interpreted as relative indicators of perceived AI literacy readiness, rather than as absolute response percentages. This approach allows comparison of readiness patterns across knowledge, skills, and attitudes, as well as between university staff and students.

Table 4. Self-assessment scores of AI literacy readiness of University Staff.

Dimension	Level 1	Level 2	Level 3	Level 4	Level 5
Knowledge (%)	78.36	73.88	59.70	58.96	54.10
Skills (%)	86.57	64.55	53.36	43.66	35.45
Attitudes (%)	64.18	81.72	63.06	72.76	70.52

Note: Values represent normalized mean scores expressed as percentages of the maximum possible score on the five-point Likert scale. They do not represent response-option percentages.

Table 5. Self-assessment scores of AI literacy readiness of students.

Dimension	Level 1	Level 2	Level 3	Level 4	Level 5
Knowledge (%)	81.37	84.80	69.44	80.23	84.80
Skills (%)	83.99	65.69	71.08	74.84	58.01
Attitudes (%)	75.16	88.24	72.71	77.29	75.65

Note: Values represent normalized mean scores expressed as percentages of the maximum possible score on the five-point Likert scale. They do not represent response-option percentages.

Across the three dimensions, the self-assessment results indicate that university staff perceived themselves as strongest at the foundational levels of AI literacy, while confidence decreased at more advanced levels related to pedagogical application, instructional design, and leadership. In the knowledge dimension, respondents reported relatively high confidence in recognizing AI tools and understanding their basic educational uses. However, lower scores at the higher levels suggest that they felt less prepared to adapt AI concepts to disciplinary contexts, design AI-enhanced tasks, and lead advanced AI-based teaching practices. In the skills dimension, this pattern was even more pronounced. Participants reported confidence in trying simple AI tools and using them for basic teaching support, but felt less prepared to integrate AI independently into teaching, design AI-supported learning workflows, or develop innovative AI-based didactic models. This indicates that skills represented the weakest aspect of their current

AI literacy profile. In contrast, the attitudes dimension remained consistently positive across all levels. Respondents reported openness toward AI, awareness of both its opportunities and risks, and a relatively strong orientation toward responsible, ethical, and human-centered use. Taken together, the results suggest that university staff positioned themselves as motivated and conceptually aware users of AI, but not yet as fully confident designers or leaders of advanced AI-supported pedagogy.

To complement and contextualize the self-assessed AI literacy levels, qualitative responses were analyzed to capture university staff perceptions of their current knowledge, skills, and needs in daily teaching practice. In terms of knowledge, respondents most often described their current level as *“an introductory understanding of AI assistants, their potential role in teaching, and the basic conditions required for their use.”* At the same time, they emphasized *“the need for a more advanced understanding of how AI can be meaningfully adapted to different disciplinary contexts and teaching purposes.”* In terms of skills, respondents indicated that although they were willing and motivated to experiment with AI, they still lacked *“the practical competence required for more complex implementation.”* The most frequently reported needs included *“concrete examples, hands-on experience, step-by-step guidance, and greater confidence in applying AI within their own subject areas.”* A frequently mentioned barrier was *“the lack of access to paid AI tools,”* which limited opportunities for experimentation and practical application and directly affected the development of higher-level skills. In terms of attitudes, the responses indicated that participants were *“generally positive and open to continued engagement with AI,”* while also maintaining a *“reflective and cautious stance regarding ethical risks, potential overreliance on technology, and the need to preserve meaningful human involvement in teaching and learning.”* Overall, the qualitative data confirm that university staff positioned themselves at an early-to-intermediate stage of AI literacy: they were motivated, aware of the relevance of AI, and open to its use, but still identified significant gaps in advanced knowledge, practical application, and pedagogically grounded implementation.

4.2. AI Literacy Readiness of Students

The AI literacy readiness of students was assessed using a five-point Likert scale (1–5), where respondents self-evaluated their level of agreement with statements corresponding to five progressive levels of competence across three dimensions: knowledge, skills, and attitudes. The scale reflects increasing levels of AI literacy, ranging from basic awareness to advanced expertise. Higher mean values indicate stronger perceived readiness to operate at a given level. Table 5 presents the self-assessment scores of AI literacy readiness among students.

Across the three dimensions, the self-assessment results indicate that students perceived themselves as confident across foundational and intermediate levels of AI literacy, while some limitations emerged at more advanced levels of application and self-directed use. In the knowledge dimension, students reported strong confidence in understanding AI tools and their basic functions, as well as their relevance for learning. However, slightly lower confidence appeared in relation to more structured conceptual understanding of AI literacy domains. Overall, the results suggest that students demonstrated not only awareness, but also the ability to engage critically with AI in their learning contexts. In the skills dimension, students reported confidence in using AI tools and integrating them into learning activities, including combining them with other learning strategies. However, they showed lower confidence in designing more advanced, structured, and self-regulated AI-supported learning workflows. This indicates that, although students are active users of AI, more complex and systematic use is still developing. In contrast, the attitudes dimension remained consistently strong. Students showed high levels of curiosity, awareness of both opportunities and risks, and a clear

orientation toward responsible, ethical, and human-centered use of AI. Taken together, the results suggest that students positioned themselves as confident and engaged users of AI in learning, but not yet as fully developed designers of advanced, self-directed AI-supported learning processes.

To complement and contextualize the self-assessed AI literacy levels, qualitative responses were analyzed to capture students' perceptions of their current knowledge, skills, and needs in daily learning practice. In terms of knowledge, students most often described themselves as *"familiar with the basic functions of AI and its role in learning."* Many reported *"regular uses of AI for explanations, summarization, coding support, quizzes, and clarification of difficult concepts."* At the same time, a recurring theme was *"uncertainty about reliability,"* especially in coding, mathematics, research-related tasks, and situations where AI may provide confident but misleading answers. Several students also noted that they were *"less confident about more conceptual aspects of AI literacy,"* including understanding the formal domains of using, creating, and managing AI responsibly, or knowing in greater depth how AI works *"behind the scenes."*

In terms of skills, students generally portrayed themselves as *"active and capable users of AI in their studies."* They frequently referred to *"using AI for summarizing lecture materials, explaining concepts in simpler terms, generating quizzes, supporting coding tasks, brainstorming, planning, note-taking, and exam preparation."* Many students emphasized that they *"can already use AI confidently for basic and intermediate learning support."* However, the responses also show that more advanced and structured use remains less developed. Students repeatedly mentioned that they *"still need support in designing their own AI-supported learning workflows,"* including creating personalized assistants or agents, maximizing prompt quality, and using AI more systematically for self-regulated learning. Another important point is that some students still *"rely on free tools only,"* or do not have access to more advanced paid functions, which may limit deeper experimentation and workflow design.

In terms of attitudes, the responses show a *"broadly positive but clearly reflective orientation toward AI."* Many students described AI as *"useful, efficient, and increasingly necessary in modern learning,"* especially for speeding up explanations, supporting understanding, and helping with difficult or time-consuming tasks. At the same time, a strong cautionary theme appeared in the comments. Students repeatedly referred to *"risks such as hallucinations, overdependence, plagiarism, privacy concerns, reduced critical thinking, and the temptation to let AI replace rather than support their own effort."* A notable pattern is that many students explicitly framed *"AI as a tool that should assist learning, not substitute for thinking, reflection, or human teaching."* Although a smaller number of responses expressed skepticism or rejection of AI, the dominant view was that AI should be used in a responsible, ethical, and human-centered way.

Taken together, the qualitative data confirm that students positioned themselves at an active but still developing stage of AI literacy. They already use AI frequently and meaningfully in their studies, especially for explanation, support, and efficiency, but they still identify important gaps in deeper conceptual understanding, advanced workflow design, and disciplined, critical use. This pattern aligns with the quantitative results, where students appeared confident in knowledge and attitudes, while more advanced skills remained comparatively less developed.

4.3. Development of the Hybrid Intelligent Assessment System Model

The empirical findings revealed a clear asymmetry between student AI use and academic staff readiness for pedagogical integration. On the one hand, students already used AI actively in their learning practices, particularly for explanation, summarization, coding support, and task efficiency. However, their use remained uneven in terms of

critical evaluation, self-regulated learning, and the structured development of more advanced AI-supported learning strategies. On the other hand, university staff demonstrated a more cautious orientation toward AI and did not yet feel sufficiently prepared to integrate it into teaching and assessment in a pedagogically grounded and ethically robust manner. This mismatch between student practice and staff readiness highlights the need for a structured framework capable of supporting both groups simultaneously. In response, the research team developed the HIAS model as a human-centered solution for the responsible integration of GenAI in higher education. As outlined earlier in the manuscript, HIAS is structured around three interdependent layers: pedagogical, governance, and technological. Together, these layers enable meaningful, ethical, and scalable implementation of AI-supported assessment and learning.

4.3.1. Pedagogical Layer

From a pedagogical perspective, the primary purpose of HIAS is to support self-regulated learning through a structured developmental pathway that combines the logic of the SOLO taxonomy with the gradual development of knowledge, skills, and attitudes. In this model, AI is not used as a substitute for teaching, but as a scaffold that helps learners progress from basic understanding toward more independent, reflective, and advanced performance. The system is designed to support students on a weekly basis, particularly in project-based and challenge-based learning contexts where progression requires continuous monitoring, guidance, and formative feedback.

A central pedagogical feature of HIAS is the use of a student personal assistant that accompanies learners throughout the course and supports the gradual development of their projects. This assistant helps students clarify weekly tasks, understand expectations, revisit course content, and practise with different types of questions, ranging from foundational tasks to more demanding, higher-order tasks. In this way, the assistant supports progression not only in factual understanding, but also in applied skills and reflective learning. The pedagogical design is intentionally aligned with structured instructional materials prepared by the professor. By grounding the AI assistant in teacher-selected slides, course texts, articles, and other relevant learning resources, and by embedding explicit instructional guidance for the large language model, the system helps reduce the risk of hallucination and improves alignment with the intended learning outcomes. This also contributes to the development of appropriate student attitudes, as the assistant models responsible AI use and reinforces the idea that AI should support, rather than replace, active learning.

The pedagogical value of HIAS also lies in the redistribution of teacher time. By delegating routine explanation, clarification, and formative practice support to AI, the model allows teachers to focus more strongly on discussion, mentoring, group supervision, and deeper human feedback. In this sense, HIAS does not weaken the teacher's role. Rather, it strengthens the teacher's pedagogical position by reducing repetitive workload and creating more space for activities that require human judgment, dialogue, and interpretation.

4.3.2. Governance Layer

The governance layer of HIAS is grounded in the principles of the EU AI Act and broader responsible AI approaches to higher education. In line with this perspective, the model does not permit AI to function as an autonomous grading authority. Instead, AI is used only for formative feedback, while all summative decisions remain under human responsibility. This distinction is central to the system. Before the class or course begins, the professor prepares the assessment logic, feedback criteria, and feedback matrices that

guide AI-generated responses. As a result, AI feedback is not arbitrary or generic, but shaped by pedagogically defined expectations and controlled instructional parameters.

Transparency is another core principle of the governance layer. Students can request that the AI system indicate the material sources used to generate a response, thereby improving explainability and trust. Responses can be linked back to predefined course resources, helping students understand where the information comes from and reducing the opacity often associated with GenAI tools. Ethical safeguards are also explicitly embedded in the model. HIAS does not use emotion recognition, biometric tracking, or invasive monitoring technologies. Only submitted student work, course-related interactions, and reflective learning artifacts are used within the educational process. Students are not expected to provide unnecessary personal information, and the system is designed to operate within strict boundaries of educational relevance and data minimization.

A further defining feature of the governance layer is the human-in-the-loop principle. Human oversight is not only present at the level of grading, but also integrated into the organization of learning activities. In the implemented course design, professors may deliver a shorter lecture segment, for example around thirty minutes, after which students work collaboratively in groups for a longer period, such as one hour. During this process, each group is given dedicated time to discuss its previous week's work directly with the professor. This means that AI may help check, structure, or support student work before class, but teacher feedback remains an essential part of the learning cycle. The model therefore preserves the centrality of human dialogue, interpretation, and pedagogical judgment.

4.3.3. Technological Layer

The technological layer of HIAS is designed to provide accessible and user-friendly AI support without displacing the teacher's central educational role. The user interface is embedded within an existing large language model environment, while the knowledge base is supported through a retrieval-augmented generation (RAG) approach. In practical terms, this means that the system draws on a predefined set of reliable course materials, such as lecture slides, books, scientific articles, and other selected resources. By grounding the AI assistant in curated academic content, the model improves response quality, helps reduce the risk of hallucination, and increases alignment with the specific learning context.

To ensure appropriate behaviour, the professor prepares a set of instructions that guide the large language model to respond in a way that reflects the intended teaching style, course logic, and pedagogical expectations. As a result, when students ask questions, they receive answers that are not only technically relevant but also aligned with how the professor would explain concepts, structure tasks, or guide learning. This contributes to continuity between classroom teaching and AI-supported study.

From an implementation perspective, the system is designed to be lightweight and accessible. The HIAS assistant can be embedded in an LMS either through an API-based connection or through a direct access link, depending on the technical setup of the course. This makes the system relatively easy to deploy across multiple learning environments while maintaining teacher control over content and behaviour. In this way, students receive an accessible AI assistant that can support them continuously in their learning, while teachers retain authority over course design, assessment logic, and educational interpretation. The technological layer therefore serves the pedagogical and governance layers rather than overriding them.

4.3.4. Synthesis of the Model

Taken together, the three layers of HIAS form an integrated response to the gaps identified in the empirical findings. Figure 1 presents the Hybrid Intelligent Assessment System (HIAS) model. Although the model is presented through distinct layers for analytical clarity, the pedagogical, governance, and technological layers should be understood as mutually interdependent rather than hierarchical.

The pedagogical layer addresses the need for structured AI-supported self-regulated learning, while the governance layer ensures ethical, transparent, and human-controlled use of AI in assessment. The technological layer provides the practical infrastructure for implementation through curated resources, prompt-guided behaviour, and accessible integration. In this way, HIAS is proposed not merely as a technological innovation, but as a pedagogically and ethically grounded model for supporting both students and teachers in the transition toward AI-enhanced higher education.

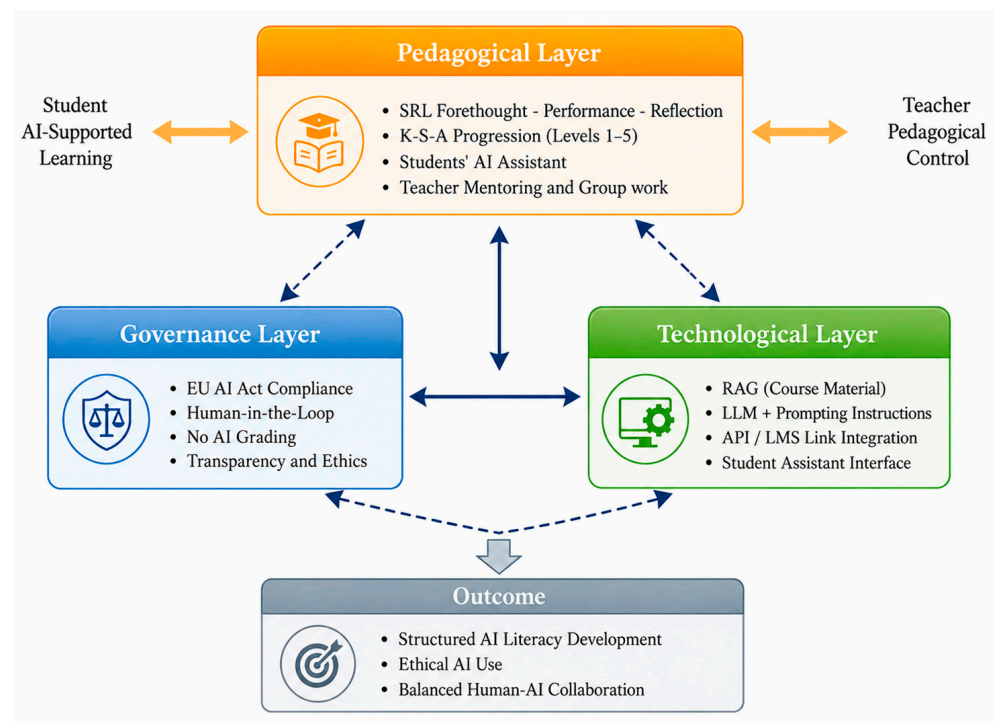


Figure 1. Hybrid Intelligent Assessment System (HIAS) Model.

To illustrate the practical application of the model, a prototype AI assistant was developed and implemented within a course at one Estonian university, Innovating Through Design Thinking and Challenge-Based Learning. The assistant enables students to interact with structured course materials and receive guided support aligned with the pedagogical framework. It operates based on curated learning resources and predefined instructional prompts, ensuring alignment with learning objectives and helping reduce the risk of unreliable or ungrounded outputs. The instructional design is structured through a weekly learning plan embedded in the large language model, which organizes each week by topic, activities, materials, student deliverables, and homework, thereby guiding both AI responses and student progression. Furthermore, the system is constrained to respond only within the scope of course-relevant topics, preventing off-topic or unrelated outputs. A representative example of this implementation is accessible via the Supplementary Materials section.

Compared with existing AI-supported assessment approaches that often focus on automated grading, feedback generation, or isolated learning analytics functions (Nikolic et al., 2023; Conijn et al., 2023; Weng et al., 2024), HIAS contributes by integrating pedagogical progression, governance safeguards, and technological implementation into a single conceptual architecture. Its distinctive contribution lies in combining SRL-oriented formative support (Molenaar et al., 2023; Steinert et al., 2024), teacher-defined assessment logic and responsible GenAI use in assessment (Perkins et al., 2024; Rakic et al., 2026), human-in-the-loop oversight and transparency requirements aligned with the EU AI Act (European Commission, 2024), course-specific knowledge grounding, and AI literacy development. In this way, HIAS is not positioned as another automated assessment tool, but as a structured model for organizing responsible human–AI collaboration in assessment and learning.

4.4. Pilot Implementation of HIAS in a Design Thinking Course

To further illustrate how the HIAS model can be operationalized in a real higher education context, a small-scale pilot implementation was conducted during the spring semester of 2026 in the 15-week elective course *Innovating Through Design Thinking and Challenge-Based Learning*. The course was selected because its project-based and challenge-based structure required continuous formative feedback, weekly task clarification, student reflection, and iterative development of individual and group project work. These characteristics made it a suitable setting for exploring how an AI-supported assistant could support the pedagogical, governance, and technological layers of HIAS in practice.

The pilot was implemented through the university's ChatGPT Edu environment, using paid institutional licences provided to lecturers and students. The AI assistant was designed as a course-specific assistant and embedded into the Moodle learning management system to ensure continuous student access throughout the semester. It was structured according to the HIAS logic. From a pedagogical perspective, it supported students in understanding course content, clarifying weekly tasks, navigating project work, and developing semester assignments. From a knowledge-base perspective, it used curated course materials provided by the lecturer, including lecture slides, books, scientific articles, weekly instructions, assignment descriptions, and other course-related resources. This functioned as a course-specific knowledge base, similar to a retrieval-augmented approach, helping align AI-generated responses with the intended course content and reducing the risk of generic or irrelevant answers. From a skills-development perspective, students were provided with weekly templates and guidance for their semester project work. From a technological perspective, the assistant was integrated into the Moodle course space, allowing students to access it in relation to each weekly learning activity.

The overall concept of the pilot was that the AI assistant should support, but not replace, the learning and assessment process. Students used the assistant to clarify course materials, understand assignment requirements, receive formative feedback, conduct preliminary checks before submitting work, and generate ideas or examples for project development. After each lecture, the assistant also provided questions based on the HIAS logic and assessment matrix, enabling students to check their understanding of the knowledge gained during the course. Importantly, the assistant was not used for autonomous grading or summative decision-making. Its role was limited to formative learning support, while the lecturer retained responsibility for mentoring, feedback, assessment interpretation, and final evaluation decisions. This implementation therefore reflected the core HIAS principle that GenAI should support human pedagogical judgment rather than replace it.

Six students actively participated in the pilot evaluation. Although the number of participants was small, the group represented different academic backgrounds, including architecture, chemical engineering, IT systems, mechatronics, and robotics. This diversity was useful for exploring how students from different disciplines experienced a course-specific AI assistant in a project-based learning environment. However, due to the small sample size, the results are interpreted as exploratory pilot feedback rather than statistical validation of the HIAS model.

The evaluation instrument was developed as part of a broader study and included several components. First, demographic information was collected to understand the participants' backgrounds. Second, students were asked how they used the Moodle-based course AI assistant and how they used ChatGPT Edu or other general-purpose AI tools. Most students reported using the course assistant primarily for clarifying assignment instructions or requirements, explaining and understanding course materials, receiving feedback on their work or solutions, and conducting pre-assessment or preliminary checks before submission. In comparison, general-purpose AI tools were mainly used for asking for ideas, examples, or possible solution approaches. Third, students evaluated their learning experience using Likert-scale items covering the main HIAS-related dimensions, including the pedagogical layer, governance layer, technological layer, feedback and pre-assessment support, and trustworthiness. Finally, open-ended questions captured students' qualitative opinions about the usefulness, limitations, and perceived value of the AI assistant.

As shown in Table 6, students evaluated the HIAS-based assistant positively across the main dimensions.

Table 6. Exploratory Student Feedback on the HIAS-Based Course Assistant.

HIAS-Related Dimension	Description	Mean Score
Pedagogical Layer	Support for understanding course materials, assignment instructions, administrative information, relevance of responses, and time-saving	4.60
Governance Layer	Possibility to check AI-generated answers, clarity of allowed use, voluntary use, access to alternatives, and availability of human support	4.20
Trust and technical support	Trust in course organization, perception of additional learning support, and trustworthiness due to connection with course materials	4.67
Feedback and pre-assessment support	Usefulness of suggestions, understandability of feedback and pre-assessment criteria, and clarity of the assistant's role in relation to the lecturer	4.61
Perceived superiority of general AI tools over the course assistant	Perception that general AI tools were more convenient or provided better answers than the course-specific assistant	2.50

Note: Values represent mean scores on a five-point Likert scale, where 1 = strongly disagree and 5 = strongly agree. Due to the small sample size ($n = 6$), the results are interpreted as exploratory pilot feedback rather than statistical validation.

The results suggest that students perceived the HIAS-based assistant as useful for supporting learning activities, clarifying course expectations, and improving access to

formative guidance between classes. The relatively high scores for feedback and pre-assessment support indicate that students valued the assistant not only as an information retrieval tool, but also as a structured learning support mechanism. At the same time, the governance-related score, while still positive, was lower than the trust and pedagogical usefulness scores. This suggests that further development should strengthen transparency, clarify the boundaries of appropriate AI use, and ensure that students understand when and how AI-generated feedback should be checked with the lecturer or other course materials.

An important finding is that students did not clearly perceive general-purpose AI tools as superior to the course-specific assistant. The relatively low mean score for the perceived superiority of general AI tools suggests that students recognized the added value of an assistant grounded in course materials, weekly tasks, and teacher-defined guidance. This supports the technological logic of HIAS, particularly the use of curated knowledge resources and instructional constraints to improve contextual relevance and reduce the risk of generic or misaligned AI responses.

The open-ended responses provide additional insight into how students experienced the assistant. Several students emphasized that it was useful for understanding expectations and navigating project work. For example, students described the most useful aspects as “asking for guidance,” understanding “expected outputs,” “getting ideas,” and “formatting my own” work. Other responses highlighted the value of the assistant for “understanding the course materials” and for “quickly understanding what” needed to be done in relation to weekly tasks. These qualitative comments support the quantitative results by showing that students valued the assistant primarily as a tool for task clarification, project guidance, idea development, and formative learning support.

Overall, the pilot implementation provides initial feasibility evidence that HIAS can be embedded into a project-based higher education course through a course-specific AI assistant connected to lecturer-provided materials, weekly learning activities, and Moodle-based access. While the small sample does not allow broad generalization, the findings illustrate how a HIAS-based assistant can support students’ individual and group project work, clarify expectations, provide formative feedback, and strengthen the connection between AI-supported learning and teacher-led assessment. The pilot also confirms the importance of continued human oversight, regular updating of course materials, clear governance rules, and careful alignment between AI-generated guidance and pedagogical intentions.

5. Discussion

5.1. Theoretical Implications

This study addresses the research question, “How can hybrid intelligent assessment methods, integrated with self-regulated learning, support the ethical adoption of GenAI in higher education?” The findings suggest that effective integration requires alignment between SRL, assessment design, and AI governance. Rather than treating AI as a standalone technological tool, the study shows that its educational value depends on structured integration into pedagogical and ethical frameworks.

First, the study extends SRL theory by positioning AI not only as a support tool, but also as a structured scaffold within the learning cycle. While prior research highlights the importance of SRL for planning, monitoring, and reflection (Kasuk et al., 2026; Banihashem et al., 2025), and recent studies demonstrate the potential of AI to support these processes (Chiu, 2024; Ng et al., 2024), there remains a gap in connecting SRL with assessment design. The HIAS model addresses this gap by embedding AI-supported feedback into a structured progression of knowledge, skills, and attitudes, thereby operationalizing SRL within assessment practices.

Second, the study contributes to AI-in-education literature by identifying an asymmetry between student use and staff readiness. Existing work highlights both the opportunities of AI for personalization and feedback (Crompton & Burke, 2023; Liao et al., 2024) and the risks of fragmented and insufficiently grounded implementation (Bearman et al., 2023; Michel-Villarreal et al., 2023). However, limited research has empirically examined how students and academic staff differ in their readiness to adopt AI. The findings show that students are already active users, while staff remain less confident in pedagogical integration, suggesting that AI adoption in higher education is uneven and requires structured support.

Third, the study advances assessment theory by bridging pedagogically grounded assessment models and AI-driven tools. While formative, self-, and peer-assessment are well established as effective approaches for supporting deep learning (Morris et al., 2021; Sillat et al., 2021), AI-based systems are often limited to automation. HIAS integrates these approaches into a unified framework by aligning AI-supported feedback with developmental models such as the SOLO taxonomy and competence-based progression (Svensäter & Rohlin, 2023; Scholze, 2025). In this way, the model reframes assessment as a guided and developmental process rather than only as outcome measurement.

Fourth, the study contributes to the literature on ethical AI by operationalizing governance principles in practice. While policy frameworks such as the EU AI Act emphasize transparency and human oversight (European Commission, 2024), their implementation in educational settings remains limited. HIAS addresses this gap by embedding human-in-the-loop control, transparency through source-grounded responses, and clear limitations on AI autonomy. This shifts the focus from abstract principles to actionable design.

Finally, the study extends AI literacy research by demonstrating that readiness is multidimensional and uneven across stakeholders. While competence frameworks emphasize knowledge, skills, and attitudes, they often lack operational clarity in educational contexts. The findings show that students may demonstrate high levels of AI use but limited critical understanding, while staff may show positive attitudes but lower practical confidence. By aligning AI literacy with a structured developmental model, HIAS provides a more actionable framework for supporting progression.

5.2. Practical Implications

The findings of this study provide several practical implications for higher education institutions, educators, and policymakers seeking to integrate GenAI into teaching and assessment in a structured and responsible manner.

First, the results indicate that universities should move beyond ad hoc or tool-driven adoption of AI and implement structured frameworks for AI-supported learning and assessment. The identified gap between student use and staff readiness suggests that institutions need coordinated strategies that support both groups simultaneously. The HIAS model offers a practical approach by combining pedagogical structure, governance mechanisms, and technological implementation into a single framework. This implies that AI integration should not be left to individual experimentation, but should be embedded within course design, assessment strategies, and institutional policies.

Second, the findings highlight the need for systematic capacity building among academic staff. While educators demonstrated positive attitudes toward AI, many lacked confidence in applying it pedagogically. Universities should therefore invest in targeted training that goes beyond technical tool use and focuses on how AI can support self-regulated learning, formative assessment, and student development. This includes supporting teachers in designing AI-assisted activities, developing feedback structures, and understanding the limitations and risks of AI in assessment contexts.

Third, the results suggest that students require structured guidance in using AI effectively, rather than unrestricted access alone. Although students already use AI extensively, their use is often efficiency-driven and may lack critical reflection and methodological depth. The HIAS approach demonstrates how this can be addressed through AI assistants aligned with course materials, weekly learning plans, and structured progression across knowledge, skills, and attitudes. This implies that AI should be integrated as part of the learning process, rather than used as an external tool without pedagogical framing.

Fourth, the study emphasizes the importance of embedding governance and ethical safeguards into educational practice. Institutions should ensure that AI is used primarily for formative support, while maintaining human control over summative assessment. Transparency, explainability, and clear communication of AI roles should be integral to course design. Ethical boundaries, such as avoiding invasive data collection and ensuring responsible use of student data, must also be explicitly defined and implemented.

Fifth, from a technological perspective, the findings suggest that effective implementation does not require complex or fully custom-built systems. Instead, it can be supported through the strategic integration of existing AI tools with curated content and instructional design. Approaches such as retrieval-augmented generation, prompt-guided behaviour, and integration with existing learning environments can enable scalable and accessible deployment. This lowers barriers to adoption and allows institutions to experiment with AI-supported learning without substantial infrastructural investment.

Finally, the study demonstrates that AI can contribute to the reconfiguration of teaching practices rather than their replacement. By supporting routine tasks such as explanation, feedback, and guidance, AI enables educators to allocate more time to high-value activities, including mentoring, discussion, and collaborative learning. This shift reinforces the role of teachers as facilitators of learning rather than only as providers of information.

At the same time, the model requires attention to implementation conditions. The implementation of HIAS depends on several factors that may influence its scalability across different institutional contexts. First, access to reliable and institutionally supported AI tools is important. If students and teachers rely only on free AI accounts, the quality, continuity, privacy conditions, and available functionalities of AI-supported learning may be uneven. Second, the development of a course-specific AI assistant requires additional teacher preparation time, particularly for selecting course materials, defining weekly instructions, preparing feedback criteria, and establishing clear rules for appropriate AI use. Therefore, HIAS should not be understood as a plug-and-play technological solution, but as a pedagogically guided implementation process that requires institutional support, teacher training, access to appropriate AI infrastructure, and time for instructional design. These requirements may be easier to meet in digitally advanced contexts such as Estonia and in technology-oriented programmes, while implementation in less digitally mature institutions or non-technical disciplines may require additional scaffolding, simpler AI literacy activities, and phased adoption.

Taken together, the theoretical and practical implications suggest that successful integration of GenAI in higher education depends on a balanced approach that combines pedagogical design, institutional support, ethical governance, and practical implementation. The HIAS model provides a concrete pathway for achieving this balance, offering a scalable and transferable approach for universities navigating the transition toward AI-enhanced education.

6. Conclusions

This study examined the readiness of university staff and students for the adoption of GenAI in higher education and addressed the identified gap through the development of the Hybrid Intelligent Assessment System (HIAS). The findings indicate a clear asymmetry: students already actively use AI in their learning processes, while academic staff, although positive in attitude, are not yet fully prepared to integrate AI pedagogically and systematically into assessment. This mismatch highlights the need for structured approaches that go beyond ad hoc or tool-driven AI adoption.

In response, this study proposed HIAS as a conceptual and practical framework structured around three interdependent layers: pedagogical, governance, and technological. The model contributes to the field by operationalizing self-regulated learning within AI-supported assessment, embedding ethical and human-in-the-loop governance aligned with the EU AI Act, and providing a scalable technological approach based on curated resources and guided AI interaction. By linking empirical findings with a structured model, the study advances current research on AI in education from fragmented applications toward integrated and responsible implementation.

Limitations and Future Research Directions

The study has several limitations. First, the empirical data are limited to the Estonian higher education context, which, while digitally advanced, may not fully represent other educational systems. Future research should therefore extend the analysis to multiple countries in order to validate the generalizability of the findings and the applicability of the HIAS model across diverse institutional and cultural settings.

A second limitation concerns the disciplinary composition of the student sample. Most student participants were enrolled in IT, software and systems development, or cybersecurity programmes. These students may have greater prior exposure to AI tools, stronger digital confidence, and more frequent experience with computational systems than students from non-technical disciplines. Therefore, the student findings should not be interpreted as fully representative of all higher education students. Instead, they should be understood as evidence from a digitally advanced and technology-oriented higher education context, which is useful for early-stage HIAS development but requires further validation across broader disciplinary settings. Future studies should examine the HIAS model with students from other fields, including humanities, social sciences, teacher education, health sciences, business, and non-technical engineering disciplines, where different forms of AI literacy support and pedagogical scaffolding may be required.

A further limitation concerns the reliance on self-assessed AI literacy, which is inherently susceptible to social desirability bias and the tendency of participants to overestimate their own competence. Future studies should therefore complement self-report measures with objective performance-based assessments or observational data to establish the validity of the findings more rigorously.

In addition, future work should move beyond readiness analysis and focus on evaluating the effectiveness and user satisfaction of the HIAS model after its implementation in real courses. This includes examining its impact on student learning outcomes, AI literacy development, and changes in teaching practices. Further research may also explore longitudinal effects, cross-disciplinary applications, and the integration of additional data sources to enhance adaptive feedback and personalization.

Overall, this study demonstrates that the successful integration of GenAI in higher education depends not on technology alone, but on its alignment with pedagogical design, ethical governance, and structured implementation. The HIAS model provides a foundation for this alignment and offers a pathway for universities seeking to adopt AI in a responsible, scalable, and educationally meaningful way.

Supplementary Materials: The following supporting information (prototype AI implemented within the course *Innovating Through Design Thinking and Challenge-Based Learning*) can be downloaded at: <https://chatgpt.com/g/g-6944007c95e881a4b70a8b785659bbdc-icy0034-innovating-through-design-thinking-and-cbl> (accessed on 20 June 2026).

Author Contributions: Conceptualization, S.R. and J.L.; methodology, S.R.; formal analysis, J.P.; data curation, S.R., E.K., J.P., and J.L.; writing—original draft preparation, S.R.; writing—review and editing, V.T. and J.L.; visualization, E.K.; supervision, V.T.; project administration, V.T.; funding acquisition, S.R. and J.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research is supported by the Estonian Research Council under the project Hybrid Intelligent Assessment System for Inclusive and Ethical GenAI Use in Higher Education (Project No. KOHTO25), implemented at Tallinn University of Technology from 1 September 2025 to 31 August 2027.

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of the University of Novi Sad, Faculty of Technical Sciences (protocol code 01-391/2 and date of approval 23 January 2026) for studies involving humans.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Data are available upon reasonable request from the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

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