Digital Intelligence and the Impact to University Education
From Learning to Co-learning Towards Understanding

Peter Sincak

Institute of Artificial Intelligence, Technical University of Kosice, Slovakia,
peter.sincak@tuke.sk,
WWW home page: https://www.petersincak.com

Abstract. Universities are entering a period in which the classical image of learning and examination is no longer sufficient. Students no longer study only with a textbook, lecture notes, a deadline, and their own memory. Increasingly, they also work with Personal AI Agents (PAIAs) that explain difficult ideas, translate disciplinary language, generate examples, simulate examiners, suggest code, support projects, and provide rapid feedback. This paper argues that the key question for universities is not whether students will use AI, but whether universities can design learning and assessment in such a way that students learn with AI while keeping judgment, responsibility, and ownership human. Building on digital intelligence, blended learning, project-based learning, question-based learning, and the Marek/Gabriela distinction between pragmatic AI builders and deeper AI architects, the paper proposes Companion-Aware Assessment as a human-centered model for higher education in the AI era. The paper keeps the formal model intentionally simple. Knowing is interpreted as a combination of learning and understanding, and the university task is to ensure that AI support stimulates understanding rather than replacing thinking. The paper also introduces a Reasoning Maturity Scale as a complement to traditional grades, emphasizing explanation, verification, transfer, and student responsibility for the results of human-PAIA interaction. The paper concludes that future universities should not limit their response to cheating prevention. They must cultivate graduates who can question AI, verify AI, collaborate with AI, and remain responsible for decisions made with AI.

Keywords: artificial intelligence in education, personal AI agents, blended learning, project-based learning, university assessment, academic integrity, digital intelligence, companion-aware assessment, reasoning maturity, Reading-to-Questions

1 Introduction

University education has long been organized around a familiar scene: a teacher, a curriculum, a group of students, and an examination intended to determine

© The Author(s) 2026
S. Árvai-Homolya et al. (eds.), *Proceedings of the 2nd Innovation in Engineering Education Conference (IEE 2026)*, Atlantis Highlights in Social Sciences, Education and Humanities 58,
https://doi.org/10.2991/978-94-6239-823-8_17

what each student has learned. The examination room became the symbol of this arrangement. Students entered alone, usually without books, peers, devices, or outside support. Their performance was interpreted as evidence of what had been internalized.

That scene is changing quickly. The change is not only that information is easier to find. The Internet already made information abundant. The deeper change is that students increasingly have access to interactive intelligence. A personal AI assistant can explain a theorem in several ways, produce examples, rehearse an oral exam, translate a text, write or debug code, suggest research questions, organize study time, challenge an argument, and give feedback in seconds. In other words, students are no longer working only with information. They are working with systems that respond, adapt, and co-produce.

The lonely student is therefore disappearing. A student with a Personal AI Agent (PAIA) is not simply a student with a tool. The student is learning inside a new cognitive ecology in which access to knowledge, confusion, motivation, uncertainty, writing, coding, and confidence are reorganized. Universities need more than bans, plagiarism detection, or general warnings. They need a pedagogy and an assessment architecture for a world in which AI assistance is normal.

The world will not wait for universities to decide whether AI is allowed. Employers will increasingly expect graduates who can use AI systems fluently but also critically. Society needs people who can work with AI without becoming intellectually passive: people who ask good questions, recognize false confidence, verify evidence, communicate uncertainty, and accept responsibility for final decisions. This is especially important in engineering, computer science, cybernetics, economics, public administration, teacher education, healthcare, and other fields in which automated recommendations may influence real people.

This paper develops an educational response around five linked ideas. First, future university education should be genuinely blended: not merely a mixture of online and face-to-face activities, but a purposeful combination of human teaching, AI-supported preparation, project work, seminars, and reflective assessment. Second, project-based learning should become more central because professional competence is demonstrated in authentic tasks, not only in isolated answers. Third, question-based learning should be strengthened because the quality of a student's question is often a more reliable sign of understanding than the fluency of a generated answer. Fourth, assessment should become companion-aware; it should acknowledge that students may learn and work with AI agents. Fifth, certification must remain human-finalized because grades, degrees, and professional trust depend on responsibility, not only performance.

The central claim is simple: if an examination can be passed by copying an AI-generated answer, the problem is not only AI; the problem is also the examination. Universities must redesign learning and assessment so that responsible AI use becomes visible and human reasoning remains assessable. This does not mean that all traditional exams should disappear. Some knowledge must still be internalized. However, the dominant culture of assessment must move from

answer reproduction toward evidence of explanation, verification, transfer, judgment, and responsibility.

The paper is deliberately conceptual. It is intended to trigger discussion about the future of universities rather than to close the discussion with a complicated measurement system. It therefore keeps the formal model simple and uses it mainly as a thinking tool for teachers, students, and institutional leaders. Interesting information about this topic can be found in a number of publications [1], [2], [3], [4]. The widespread adoption of generative AI chatbots since 2022–2023 has led to a rapid expansion of research on AI-assisted learning.

2 Digital Intelligence is Changing University Education

2.1 Digital intelligence as a socio-technological environment

Digital intelligence is used here to describe the integration of artificial intelligence, cloud computing, networked devices, data infrastructures, virtual and augmented environments, and new business models that automate parts of physical and mental work. This interpretation continues the cybernetic tradition of thinking about communication, control, feedback, and intelligent systems. For students and teachers, AI rarely appears as one isolated application. It appears as an ecosystem: copilots, chatbots, retrieval systems, coding assistants, simulators, translators, recommender systems, productivity platforms, and workflow automation tools. These systems are becoming part of everyday study, research, administration, and professional work. The conceptual roots of this interpretation of digital intelligence can be traced to the cybernetic tradition and can be found in [5].

The transformation is not limited to informatics or engineering. It affects law, medicine, economics, teacher education, humanities, social sciences, public administration, and the arts. A graduate entering professional life will not only be asked what they know. They will be asked whether they can work with intelligent systems, detect errors, explain decisions, manage uncertainty, communicate with people outside their discipline, and remain accountable when automated recommendations are incomplete or wrong.

For universities this creates a double responsibility. They must prepare students for an AI-rich world, but they must also protect the habits of thought that higher education is meant to cultivate. AI can make students faster, but speed is not the same as understanding. AI can make texts fluent, but fluency is not the same as judgment. AI can make projects look impressive, but presentation is not the same as validated knowledge.

2.2 Personal AI Agents as learning companions

A Personal AI Agent is a system that supports an individual across tasks, contexts, and time. In education, however, the word agent may be too narrow if

it suggests only task execution. Students often experience these systems as explainers, tutors, critics, translators, planners, rehearsal partners, organizers, and sometimes as psychologically safe first listeners.

This companion role matters. A student may ask an AI agent a basic question without embarrassment. The student may request the same explanation several times, at different levels of difficulty, without feeling judged. A student who is blocked by a blank page may use AI to begin. A student who is anxious about an oral exam may rehearse with an artificial examiner before facing a human one. These are not small changes. They alter the emotional and cognitive conditions of learning.

The risks are equally real. Personal AI systems can hallucinate, simplify too much, flatter the user, standardize thought, produce plausible falsehoods, and generate polished text that hides weak understanding. The task of the university is therefore not to celebrate AI naively, nor to pretend that it can be removed from student life. The task is to teach students how to work with AI critically, transparently, and responsibly.

The guiding principle of this paper is:

AI may assist the process, but the student must own the reasoning.

Ownership does not mean that the student performed every micro-action alone. That would be unrealistic in modern professional work. Ownership means that the student can explain the final answer, defend the method, verify the evidence, identify limitations, disclose assistance, and accept responsibility for the decision.



Fig. 1. An emerging situation in university education in which students and teachers increasingly use Personal AI Agents. Individuals without appropriate AI literacy may be disadvantaged in future professional environments. Universities should therefore cultivate a responsible and productive relationship among teachers (mentors), students, and their PAIAs.

Figure 1 illustrates this new classroom situation. The teacher remains central, but not as the only source of information. The teacher increasingly becomes the designer of inquiry, the mentor of judgment, and the person who reconnects digital assistance with human reasoning.

2.3 The Marek/Gabriela distinction

The Marek/Gabriela distinction is useful for thinking about AI education. Marek represents the pragmatic builder: the person who assembles data pipelines, connects application programming interfaces, uses open-source repositories, prototypes systems, and delivers working models quickly. Gabriela represents the deeper architect: the person who understands mathematical foundations, model limitations, uncertainty, failure modes, governance, ethics, and socio-technical consequences. A healthy AI ecosystem needs both. Universities should not underestimate pragmatic builders; prototyping is a real and necessary competence. At the same time, routine Marek-type tasks are increasingly supported by AI systems themselves. Code can be generated, interfaces can be connected, documentation can be drafted, and prototypes can be assembled more quickly than before. This raises the value of Gabriela-type judgment. The harder questions are no longer only whether something can be built, but why it works, when it fails, who may be harmed, what must be verified, and which decision must remain human.

This distinction reframes university education. Bachelor-level programs may reasonably emphasize practical AI fluency, prototyping, and responsible tool use. Master and doctoral programs must go further: explanation, abstraction, validation, uncertainty, ethics, and governance should become central outcomes. In the long term, the most valuable graduates will combine both capacities: they will build like Marek and question like Gabriela. This concept was mentioned in 2019 (before of chatbots era) and anticipated a near future of human–AI collaboration; see [6].

3 Pedagogical Foundations for AI-Era Universities

3.1 Blended learning as a human-agent design

Blended learning is often defined as a combination of online and face-to-face learning. In the AI era, this definition should be expanded. Blended learning becomes a human-agent design in which online work, AI-supported preparation, classroom dialogue, project activity, feedback, and assessment are deliberately connected [7], [8].

Online time should not mean passive video consumption. It can include AI-supported reading, simulation, retrieval practice, self-testing, question generation, exploratory coding, preparation for seminar work, and reflection on confusion. Face-to-face time becomes more valuable, not less, because it can be used for disagreement, oral explanation, collective problem solving, experiments, mentoring, and the development of trust.

The blended course of the future is not a course where lectures are simply uploaded to a platform. It is a course where each learning mode has a purpose. AI-supported preparation helps students identify gaps. The human classroom creates intellectual friction and social accountability. Project work requires integration and implementation. Assessment collects evidence across all these spaces.

A useful design principle is:

Use AI for preparation and iteration; use human teaching for judgment, challenge, dialogue, and certification.

3.2 Project-based learning as evidence of competence

Project-based learning matters because AI-rich professional work rarely consists of producing one answer under isolation. Students must define problems, coordinate roles, search and verify sources, build artifacts, test prototypes, document decisions, and present defensible conclusions. AI can accelerate many parts of this process, but it cannot legitimately replace human responsibility for framing the problem, choosing evidence, interpreting results, and making the final judgment.

Project-based learning also makes the Marek/Gabriela distinction visible. In a team, one student may build the prototype, another may test assumptions, another may analyze limitations, and another may identify ethical risks. A good assessment system should value all of these contributions. It should not reward only the polished final artifact. It should also evaluate the process by which the artifact was built, challenged, revised, and defended [9], [10], [11], [12].

3.3 Question-based Learning Using Reading-to-Questions Approach

Question-based learning is especially important in the age of generative AI. When answers are cheap, questions become more valuable. The Reading-to-Questions (R2Q) approach changes reading from passive intake into inquiry. Students read with the aim of producing claims, assumptions, counter-evidence, diagnostic questions, and seminar agendas.

An R2Q-oriented course asks students to move through a sequence:

1. What is being claimed?
2. What assumptions are hidden?
3. What evidence supports the claim?
4. What evidence challenges the claim?
5. What would make the claim false?
6. How does the concept transfer to a new context?
7. What should a responsible human decide?

AI may help students identify claims or generate possible questions, but students must select, improve, and defend the questions. This matters because the quality of a question often reveals the structure of a student's understanding.

A weak learner asks for an answer. A stronger learner asks what is uncertain, what is assumed, what is missing, and what would change the conclusion.



Fig. 2. From printed reading to R2Q-supported digital reading. The central question is whether PAIA-supported reading can stimulate human thinking rather than replace it.

Figure 2 shows the reading transformation that motivates R2Q. The point is not simply to put a PDF on a screen. The deeper question is whether digital reading with PAIA can help students generate better questions, test assumptions, and enter seminars with more active thinking.

4 A Simple Conceptual Formalization of Human–PAIA Co-learning

The following model is intentionally simple. Its purpose is not to reduce education to mathematics, nor to suggest that student development can be captured by one formula. Its purpose is to offer a compact conceptual language for discussing what universities should protect and assess when students learn with Personal AI Agents. Very interesting ideas can be found here [13], [14], [15].

4.1 Knowing, Learning, and Understanding

Let K denote a student's operational knowing in a course or module. Knowing can be understood as a relation between Learning L and Understanding U.

Learning includes exposure, memory, practice, recall, and procedural fluency. Understanding includes explanation, justification, critique, transfer, and responsible judgment. So we can state that human knowledge K is based on human learning L and human understanding U.

$$K = L + U. \tag{1}$$

Table 1. Pedagogical shift required by AI-supported university learning.

Dimension	**Traditional emphasis**	**AI-era emphasis**
Role of teacher	Main source of explanation and content	Designer of inquiry, mentor of judgment, evaluator of reasoning
Role of student	Receiver and reproducer of knowledge	Questioner, verifier, project worker, responsible co-thinker
Learning environment	Lecture, textbook, final exam	Blended ecosystem of seminars, projects, AI agents, portfolios, and defense
Assessment evidence	Correct answer and memory reproduction	Explanation, verification, transfer, provenance, and ownership
Academic integrity	Detection of prohibited help	Transparent design of allowed, limited, and prohibited AI use

Estimating these variables is difficult because their interpretation is domain-specific and depends partly on the assessment context and evaluator judgment. Equation (1) is not a claim that learning and understanding are independent. It is a pedagogical reminder that universities should not evaluate only stored information or polished output. They should also evaluate whether students can explain, verify, and transfer what they claim to know.

Let T denote the effort budget: attention, time, and cognitive work. A course objective J can be described as knowing per unit effort, with Understanding weighted more strongly than Learning:

$$J = \frac{w_L L + w_U U}{T}, \qquad w_U > w_L. \tag{2}$$

Equation (2) expresses a normative position. In university education, understanding should receive more weight than recall, especially when students have access to tools that can retrieve, summarize, and generate text quickly. For practical discussion, L, U, and K may be normalized to the interval $[0, 1]$ at the level of a topic, course, or assessment task:

$$K = w_L L_+ w_U U, \qquad L, U \in [0, 1], w_L + w_U = 1 \tag{3}$$

Normalization prevents a common mistake: assuming that more activity automatically means more knowing. A long AI conversation may produce little understanding if the student does not verify, transfer, or defend the reasoning.

5 Companion-Aware Assessment

Companion-Aware Assessment starts from a realistic premise: students may use personal AI assistants, but the assistant must not replace the student. Assessment should therefore reveal the quality of the student's understanding, judgment, and responsibility. The model should not be unnecessarily complicated. It can begin with simple observation of questions, explanations, verification, transfer, and ownership [16], [17], [18], [19], [20], [21].

5.1 Use of Personal Agents

There are two basic options for the use of Personal AI Agents in university learning. Both options are already possible, and both will influence assessment, academic integrity, and the role of the teacher.

Option 1: Student-owned PAIA. In this scenario, each student uses their own PAIA independently from the university. The student may choose the tool, the style of interaction, the prompts, the language, and the level of support. This option reflects the real world because students will use AI tools outside the university whether the institution formally supports them or not. It respects student autonomy and may encourage experimentation. However, it also creates difficulties. The teacher cannot see how the student used the agent, what questions were asked, what misunderstandings were reinforced, or whether the final work represents genuine understanding. Figure 3 summarizes the main strength and weakness of the student-owned model. It is realistic and encourages experimentation, but it makes the process of reasoning partly **invisible** to the teacher.

Option 2: University-based PAIA. In this scenario, each student can use only a university-based PAIA for selected learning and assessment activities. This system could be understood as an intelligent agent-based Moodle or a university learning environment that supports and monitors interaction with the student. It would not only provide answers. It would observe student questions, estimate the level of understanding, personalize support, and initiate Human-AI Socratic Question Generation. The goal is not surveillance for its own sake, but pedagogical visibility. The teacher or mentor can see where students are struggling and can react before the final examination.

A university-based PAIA could force productive interaction in a positive sense. For example, when a student asks for a final answer too quickly, the system may respond with a question: What concept from the lecture applies here? What assumption do you need to check? Can you explain why this answer should be valid? In this way, the agent supports the student but also keeps the student intellectually active.

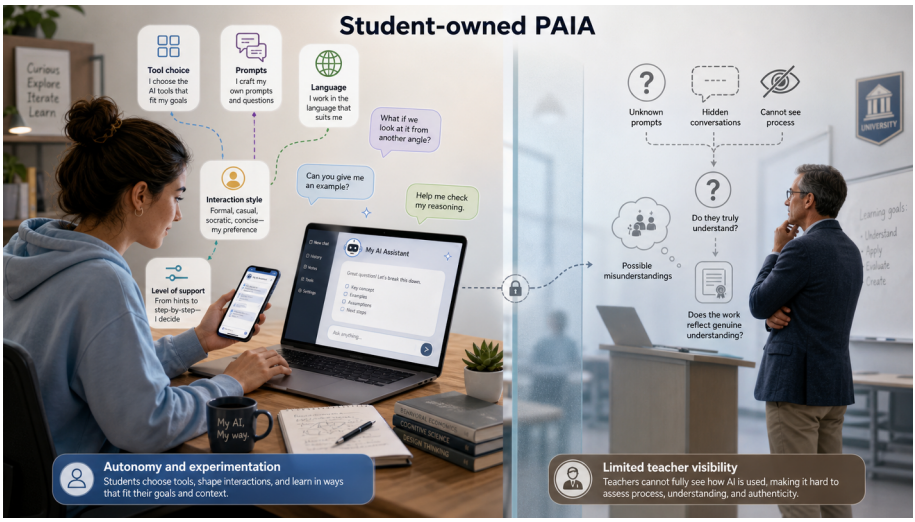


Fig. 3. Student-owned PAIA. The student has autonomy to choose tools, prompts, language, interaction style, and level of support, but the teacher has limited visibility into the learning process and cannot easily judge whether the final work reflects genuine understanding.

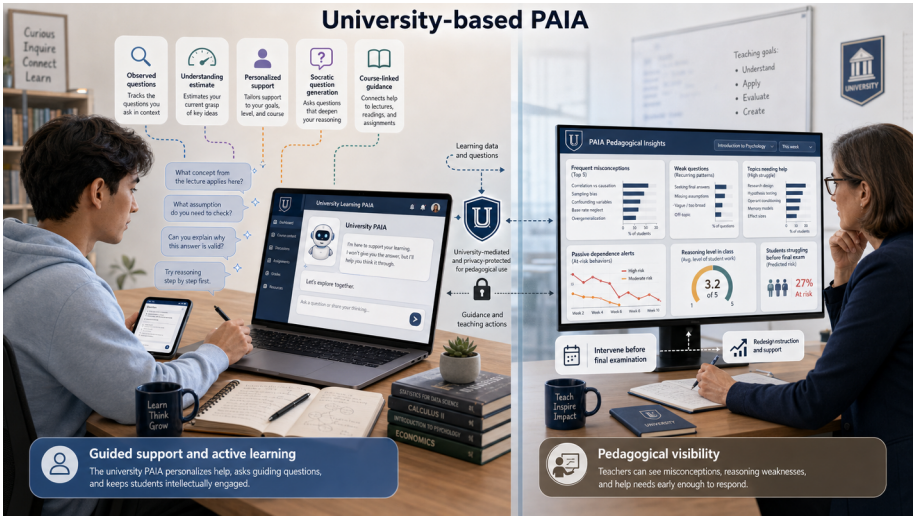


Fig. 4. University-based PAIA. The university learning environment can guide student reasoning through course-linked prompts, Human-AI Socratic Question Generation, and personalized support, while giving the teacher pedagogical visibility into misconceptions, weak questions, passive dependence, and topics that need intervention before the final examination.

The teacher or mentor would receive information about the level of reasoning in the class. Such information may include frequent misconceptions, weak questions, topics where students repeatedly need help, or students who show signs of passive dependence on generated answers. This would allow the teacher to redesign the next seminar, create a short clarification activity, or provide targeted mentoring.

Figure 4 illustrates the second option. The aim is not surveillance for its own sake, but a learning environment in which the teacher can react earlier and the student is encouraged to remain intellectually active.

The two options should not be treated as enemies. A realistic university may combine them. Students will use private tools in their lives, but universities may require institutional PAIA use for selected tasks, especially where the learning process itself must be visible.

For assessment, the university-based PAIA opens a new possibility. Instead of judging only the final answer, teachers can evaluate patterns of student interaction: the quality of questions, willingness to revise, ability to respond to Socratic prompts, and movement from superficial to deeper understanding. This makes assessment less dependent on one final product and more connected to the development of thinking.

However, this monitoring must be interpreted carefully. The purpose is not to watch students as objects of control. The purpose is to make reasoning visible enough for teaching. A university-based PAIA should monitor learning-relevant signals, not private life. It should help teachers detect when students are becoming passive, when they ask only for final answers, when they repeatedly misunderstand a core concept, or when they avoid verification. Such information should be used to support students earlier, not to punish them mechanically.

Table 2. Two institutional options for PAIA use.

Aspect	**Student-owned PAIA**	**University-based PAIA**
Control	Chosen and controlled by student	Provided or approved by university
Visibility	Low visibility for teacher	Learning-relevant interaction can be monitored
Personalization	Personal but not aligned with course design	Personal and aligned with course goals
Assessment value	Difficult to verify process	Questions, misconceptions, and reasoning patterns can inform assessment
Risk	Hidden substitution, unequal tools	Privacy, governance, and institutional responsibility
Main advantage	Autonomy and realism	Pedagogical feedback and teacher awareness

The most important boundary remains student responsibility. A PAIA can suggest, explain, ask, warn, and summarize, but the outcome of Human-PAIA interaction must remain the student's responsibility. The student should be able to say: this is what I asked, this is what I accepted, this is what I rejected, this is how I verified it, and this is why I stand behind the final answer.

Table 3. Learning-relevant monitoring signals in a university-based PAIA.

Signal	Short meaning	Pedagogical use
Question pattern	Type and depth of student questions	Adapt prompts and seminar discussion
Misconceptions	Repeated conceptual errors	Redesign explanations and examples
Socratic response	Ability to reason after guiding questions	Provide mentoring and practice
Verification behavior	Checking sources, assumptions, and outputs	Strengthen responsible AI use
Passive dependence	Asking for answers without reasoning	Intervene early; remind responsibility

Table 3 illustrates the difference between surveillance and pedagogical visibility. The teacher should not need to read every private sentence written by the student. The teacher needs interpretable educational signals: where the class is struggling, where reasoning is weak, and where responsibility is being outsourced to AI. Similar studies can be found [22], [23], [24], [25].

6 Reasoning Maturity Scale

Traditional A-B-C-D-E-FX grading is administratively useful but intellectually limited. It tells us whether a student performed well according to a scoring scheme, but it does not tell us what kind of thinker the student is becoming. In an AI-rich environment, this weakness becomes more serious.

Two students may both receive a B. One may have memorized efficiently and reproduced expected answers. The other may have asked original questions, detected weak AI-generated reasoning, transferred a concept to a new context, and defended a decision under pressure. The same grade may therefore hide different forms of intellectual development.

The Reasoning Maturity Scale complements traditional grading by reporting the student's level of intellectual agency. It does not replace grades immediately. Instead, it adds a second language for discussing the development of thinking: reproduction, explanation, verification, transfer, and responsible co-thinking with AI.

Table 4. Reasoning Maturity Scale for AI-era university assessment.

Level	Name	Description	Indicative relation to traditional scale
R0	Not yet responsible	Cannot explain, verify, or take responsibility; depends passively on AI or memorized fragments.	FX
R1	Reproducer	Repeats definitions, formulas, procedures, or known examples with limited explanation	E/D
R2	Explainer	Explains concepts in own words and shows basic understanding	D/C
R3	Verifier	Checks correctness and detects weak assumptions, hallucinations, or unsupported claims	C/B
R4	Transfer thinker	Applies concepts to new situations, changed conditions, or other domains.	B/A
R5	Responsible co-thinker	Uses AI critically while questioning, rejecting, verifying, deciding, and defending	A

Table 4 makes explicit that the future examination should not ask only whether the final answer is correct. It should also ask whether the student can explain the answer, verify it, transfer it, and take responsibility for the Human-PAIA process that produced it. A student who uses PAIA well is not a passive recipient of generated text. The student is a responsible co-thinker who directs the agent, challenges it, checks its output, and remains accountable for the final decision.

This is especially important when the university-based PAIA monitors reasoning patterns. Monitoring should not mean that the agent becomes the judge of the student. Rather, the agent can provide evidence for human teachers: the kinds of questions asked, the points where the student requested help, the moments where the student accepted or rejected suggestions, and the depth of explanation after prompting. The final interpretation of this evidence should remain human, contextual, and educational.

The scale also protects students. It tells them what kind of intellectual growth is expected. The goal is not simply to hide AI use or to produce a polished answer. The goal is to move upward: from reproduction to explanation, from explanation to verification, from verification to transfer, and finally to responsible co-thinking with AI.

7 Blended Learning Implementation Model

A practical AI-era course can be organized as a blended learning cycle. Before class, students work with readings, videos, retrieval systems, and personal AI agents. They generate questions, identify unclear concepts, produce a short

claim-evidence map, and prepare a micro-reflection. During class, the teacher uses student questions to organize seminars, debates, live coding, case analysis, experiments, or peer explanation. After class, students apply concepts in projects, document decisions, and receive feedback from peers, teachers, and AI systems.

This cycle changes the teacher's role but does not reduce its importance. The teacher is no longer the only source of information. However, the teacher becomes more important as a designer of learning situations, guardian of standards, mentor of judgment, and evaluator of human reasoning.

Table 5. Three-phase blended learning cycle with PAIA.

Phase	**Mode**	**Student activity**	**Teacher activity**	**Evidence generated**
Pre-class	online, agent-supported	R2Q reading, AI dialogue, self-test, confusion log	Curates materials and prompts.	Questions, claim maps, micro-reflections
In-class	Human-centered seminar	debate, mutual explanation, experiment, oral reasoning	Challenges, moderates, diagnoses misconceptions	Participation, live reasoning, short artifacts
Post-class	Transfer and project work	Applies concepts, builds artifacts, and documents decisions	Gives feedback, samples defenses	Project logs, provenance, revision evidence

7.1 Reading-to-Question as a Pre-class Protocol

Students are using digital reading and follow-up questioning to increase the effectiveness of knowledge acquisition. The reading-to-Questions pipeline can be used as a pre-class protocol:

1. **Ingestion.** Students receive or select a text, dataset, code fragment, or case.
2. **Claim distillation.** Students identify main claims, assumptions, and definitions.
3. **Contrastive sourcing.** Students find supporting and challenging sources.
4. **Human-AI Socratic Question Generation.** Students produce questions at different levels of difficulty, supported but not replaced by PAIA.
5. **Diagnostics.** Students identify possible errors, confusions, or hallucinations.
6. **Seminar orchestration.** Teachers and students use questions to structure class discussion.

The pipeline can be supported by AI, but the output must be curated by students. The question agenda becomes an assessment artifact. Teachers can

evaluate novelty, depth, testability, relevance, and ethical awareness without turning the course into a complex scoring machine. Very interesting reports are in [26], [25], [27].

7.2 Simple assessment signals in the blended model

The simplified model does not require a long mathematical scoring system. It can begin with a small set of observable signals: quality of questions, ability to explain in one's own words, ability to identify uncertainty, willingness to revise, and ability to apply a concept in a new situation.

In a university-based PAIA environment, these signals can be summarized for the teacher. For example, a teacher may see that many students ask only factual questions, few students challenge assumptions, and most students fail to transfer the concept to a new case. This is not a final grade. It is a pedagogical signal that helps the teacher decide what to do next.

8 Inspirations for University Policymakers

Universities need clear AI policies, but policy must support learning rather than only surveillance. Several principles follow from the proposed model.

1. Universities should not pretend that AI is absent. Students already use AI or soon will.
2. Policies should distinguish assistance from substitution. Assistance supports thinking; substitution hides the absence of thinking.
3. Universities should decide when private PAIA use is acceptable and when university-based PAIA is required.
4. Assessment should be redesigned before surveillance is expanded. Detection tools alone cannot solve a pedagogical design problem.
5. AI use should be made visible through simple declarations or learning logs when appropriate.
6. Foundational knowledge should still be protected through short no-agent activities when necessary.
7. Questions, explanations, verification, transfer, and oral defense should become normal evidence of learning.
8. Equity requires baseline access to approved tools and clear rules.
9. Teachers need training, rubrics, examples, and institutional time.
10. Certification must remain human-finalized: AI may recommend, summarize, or check, but grades and ethical decisions should remain the responsibility of qualified humans.

These principles also change the meaning of academic integrity. In the past, integrity was often imagined as isolation: the honest student works alone. In the AI era, integrity must be reimagined as accountable collaboration. The honest student may use AI but discloses assistance, verifies claims, rejects weak suggestions, and accepts responsibility for final reasoning. See 2026 reports on this topic [28], [29], [30], [31].

9 Risks, Students' Responsibility, and Limits

The proposed model has risks. Students may become dependent on AI. The safeguards are no-agent micro-tests, oral explanation, transfer tasks, and explicit verification. AI may produce false information. The safeguards are source checking, error-detection tasks, and human discussion.

Recent studies strengthen this concern. Reviews of generative AI in higher education assessment argue that assessment must be redesigned around self-regulated learning, responsible learning, AI literacy, and integrity rather than only around the detection of prohibited use. The Artificial Intelligence Assessment Scale also shows that universities need transparent levels of permitted AI use so that students and teachers understand when AI is prohibited, limited, supported, or integrated into assessment. Empirical work on student and educator perceptions similarly suggests that assessment should focus more on learning processes, higher-order thinking, and authentic application.

The education of students for Human-PAIA co-learning must therefore be handled with a high level of responsibility. Students will be responsible for the output of this co-learning, even when the final text, code, explanation, or design has been shaped by PAIA. A student should not be allowed to hide behind the statement that AI generated it. The student must be able to explain the work, verify the reasoning, identify the limits, and accept responsibility for the final decision. This is the moral and intellectual core of companion-aware assessment.

This responsibility is also important because authentic or project-based assessment alone may not be sufficient to protect academic integrity. Recent evidence indicates that generative AI can produce work that is difficult for markers to distinguish from human-generated authentic assessment submissions, which means that universities cannot rely only on the apparent authenticity of a task. The assessment design must require visible reasoning, social or oral performance, process evidence, and defense of decisions.

A university-based PAIA also introduces privacy and governance questions. Monitoring student questions may raise compliance and governance issues under the GDPR and the EU AI Act. Educational transparency should not become excessive surveillance. Pedagogical visibility should support human thinking, not replace it with automated control.

Generative AI literacy is becoming an assessable competence in its own right. Recent work on a Generative AI Literacy Assessment Test shows that self-reported AI competence is not enough; students need measurable ability to understand, evaluate, and use GenAI effectively. This supports the argument that universities should explicitly teach students how to co-learn with PAIA rather than assume that technical access automatically produces mature use.

Finally, the simple equations in this paper should not be mistaken for mechanical truth machines. They are design scaffolds. Their value lies in making assumptions visible and discussable. Teachers and departments must still exercise professional judgment. The final evaluation of student responsibility, reasoning maturity, and Human-PAIA interaction must remain a human academic responsibility.

10 Discussion

The future university will not be only digital, and it will not be only physical. It will be a blended human-agent institution. Students will use AI to prepare, rehearse, write, simulate, code, translate, and explore. Teachers will design learning situations where students must explain, verify, transfer, and defend. Assessment will become more continuous, more evidence-based, and more companion-aware.

This transformation is cultural as much as technical. Universities have often treated assessment as a controlled moment in which help is removed. That logic still has a place for foundational knowledge, but it cannot remain the dominant model. In real professional work, people rarely act without tools, documents, colleagues, or intelligent systems. The relevant question is whether they can use support responsibly.

This also changes the meaning of excellence. The excellent student is not the one who produces the most fluent text. The excellent student is the one who can use powerful tools while remaining intellectually awake. Such a student asks good questions, detects errors, transfers concepts, communicates uncertainty, and makes responsible decisions.

The Marek/Gabriela distinction is useful here. Universities should educate Mareks who can build and Gabrielas who can understand deeply, but the best graduates will increasingly combine both. They will prototype quickly and critique rigorously. They will use AI and question AI. They will cooperate with agents and remain responsible humans.

11 Conclusion

The university was built for a world in which knowledge was relatively scarce, teachers were the main gateway to expertise, and students were assessed largely as isolated individuals. That world is ending. The new student is accompanied by personal AI assistants that can explain, coach, translate, challenge, organize, and support learning.

This does not make the teacher obsolete. It makes the teacher's higher role more visible. Teachers are needed to cultivate judgment, responsibility, intellectual honesty, disciplinary standards, and human meaning. Universities must therefore redesign assessment. The written exam cannot remain only a ritual of isolation if real learning and real work are becoming companion-based.

Companion-Aware Assessment does not ask students to pretend they live in the past. It asks them to become responsible thinkers in the present. In some contexts, students will use their own private PAIAs. In other contexts, universities may need to provide their own intelligent PAIA environment that supports, challenges, and records learning-relevant interaction.

The formal proposal expresses the same requirement simply. Knowing is not only Learning; it also includes Understanding. AI is educationally useful when

it increases understanding, not when it only accelerates production. Future universities should therefore evaluate not only what students answer, but how they question, verify, transfer, decide, and defend.

Students are no longer learning alone; universities must take this new reality into account. Otherwise, assessment risks becoming disconnected from the ways in which students learn and graduates will work in an AI-rich society. The goal of this paper is to trigger deeper thinking about this transformation for the benefit of the new generation that will live, learn, and work in an AI-based era.

We should return to a wisdom expressed more than 2,500 years ago by the Chinese philosopher Confucius (551–479 BC): **"Learning without thought is labor lost; thought without learning is perilous."** In the era of Personal AI Agents, this warning becomes even more important than before because students may gain access to fluent answers without developing the thinking needed to understand, verify, and responsibly use them. It is interesting for academics to read [32] especially for moral, wisdom, and human-centered rethinking of education.

Declarations

The author remains responsible for the final text, arguments, and conclusions. Author was using PAIA for text polishing and formatting. Author was using PAIA, ChatGPT plus for text polishing and formatting.

Symbols

Symbol	Meaning
AI	Artificial Intelligence
PAIA	Personal AI Agent
RAG	Retrieval-Augmented Generation
R2Q	Reading-to-Questions pipeline
QBL	Question-Based Learning
PBL	Project-Based Learning
K	Knowing
L	Learning component: exposure, memory, practice
U	Understanding component: explanation, justification, transfer, critique
T	Effort budget: attention, time, and cognitive work
J	Knowing per unit effort objective
w	Weights

References

1. Wayne Holmes, Maya Bialik, and Charles Fadel. *Artificial Intelligence in Education: Promises and Implications for Teaching and Learning*. Boston, MA: Center for Curriculum Redesign, 2019.
2. Neil Selwyn. *Should Robots Replace Teachers? AI and the Future of Education*. Cambridge, UK: Polity, 2019.
3. European Parliament and Council of the European Union. *Regulation (EU) 2016/679 of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data (General Data Protection Regulation)*. Official Journal of the European Union, L 119, pp. 1–88. May 4. 2016.
4. European Parliament and Council of the European Union. *Regulation (EU) 2024/1689 of 13 June 2024 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act)*. Official Journal of the European Union, 2024/1689. July 12. 2024.
5. Norbert Wiener. *Cybernetics: Or Control and Communication in the Animal and the Machine*. New York: John Wiley & Sons, 1948.
6. Peter Sincak. *Quo Vadis AI*. Presentation at SlovakiaTech Forum-Expo, Kosice, Slovakia, use English subtitles, video made in 2019 before chatbot Era. 2019. URL: https://www.youtube.com/watch?v=V-jGJH5gQzg.
7. Benjamin S. Bloom. "The 2 sigma problem: The search for methods of group instruction as effective as one-to-one tutoring". In: *Educational Researcher* 13.6 (1984), pp. 4–16. DOI: 10.3102/0013189X013006004.
8. D. R. Garrison and Heather Kanuka. "Blended learning: Uncovering its transformative potential in higher education". In: *The Internet and Higher Education* 7.2 (2004), pp. 95–105. DOI: 10.1016/j.iheduc.2004.02.001.
9. Fengchun Miao and Wayne Holmes. *Guidance for Generative AI in Education and Research*. Paris: UNESCO, 2023.
10. European Commission. *Guidelines on the Ethical Use of Artificial Intelligence and Data in Teaching and Learning for Educators*. Luxembourg: Publications Office of the European Union, 2026.
11. E. Woodruff. "AI detection of human understanding in a Gen-AI tutor". In: *AI* 5.2 (2024), pp. 898–921. DOI: 10.3390/ai5020045.
12. R. F. Kizilcec et al. "Perceived impact of generative AI on assessments: Comparing educator and student perspectives in Australia, Cyprus, and the United States". In: *Computers and Education: Artificial Intelligence* 7 (2024), p. 100269. DOI: 10.1016/j.caeai.2024.100269.
13. M. Perkins, J. Roe, and L. Furze. "Reimagining the Artificial Intelligence Assessment Scale (AIAS): A refined framework for educational assessment". In: *Journal of University Teaching and Learning Practice* 22.7 (2025). DOI: 10.53761/rrm4y757.
14. A. K. Kofinas, C. H. H. Tsay, and D. Pike. "The impact of generative AI on academic integrity of authentic assessments within a higher education context". In: *British Journal of Educational Technology* 56.6 (2025), pp. 2522–2549. DOI: 10.1111/bjet.13585.

15. Y. Jin et al. "Generative AI in higher education: A global perspective of institutional adoption policies and guidelines". In: *Computers and Education: Artificial Intelligence* 8 (2025), p. 100348. DOI: 10.1016/j.caeai.2024.100348.
16. L. Furze et al. "The AI Assessment Scale (AIAS) in action: A pilot implementation of GenAI-supported assessment". In: *Australasian Journal of Educational Technology* 40.4 (2024), pp. 38–55. DOI: 10.14742/ajet.9434.
17. N. Ashok Kumar and A. Lan. "Improving Socratic question generation using data augmentation and preference optimization". In: *Proceedings of the 19th Workshop on Innovative Use of NLP for Building Educational Applications (BEA 2024)*. Mexico City, Mexico: Association for Computational Linguistics, 2024, pp. 108–118.
18. C. Gonsalves. "Addressing student non-compliance in AI use declarations: Implications for academic integrity and assessment in higher education". In: *Assessment & Evaluation in Higher Education* 50.4 (2025), pp. 592–606. DOI: 10.1080/02602938.2024.2415654.
19. J. Walton et al. "How university students work on assessment tasks with generative artificial intelligence: Matters of judgement". In: *Assessment & Evaluation in Higher Education* (2025), pp. 1–17. DOI: 10.1080/02602938.2025.2570328.
20. G. Ilieva et al. "A framework for generative AI-driven assessment in higher education". In: *Information* 16.6 (2025), p. 472. DOI: 10.3390/info16060472.
21. E. D. L. Evangelista. "Ensuring academic integrity in the age of ChatGPT: Rethinking exam design, assessment strategies, and ethical AI policies in higher education". In: *Contemporary Educational Technology* 17.1 (2025), ep559. DOI: 10.30935/cedtech/15775.
22. Q. Xia et al. "A scoping review on how generative artificial intelligence transforms assessment in higher education". In: *International Journal of Educational Technology in Higher Education* 21 (2024), p. 40. DOI: 10.1186/s41239-024-00468-z.
23. M. Perkins et al. "The Artificial Intelligence Assessment Scale (AIAS): A framework for ethical integration of generative AI in educational assessment". In: *Journal of University Teaching and Learning Practice* 21.6 (2024). DOI: 10.53761/q3azde36.
24. K. Bittle and O. F. El-Gayar. "Generative AI and academic integrity in higher education: A systematic review and research agenda". In: *Information* 16.4 (2025), p. 296. DOI: 10.3390/info16040296.
25. Y. Jin et al. "GLAT: The generative AI literacy assessment test". In: *Computers and Education: Artificial Intelligence* 9 (2025), p. 100436. DOI: 10.1016/j.caeai.2025.100436.
26. N. McDonald et al. "Generative artificial intelligence in higher education: Evidence from an analysis of institutional policies and guidelines". In: *Computers in Human Behavior: Artificial Humans* 3 (2025), p. 100121. DOI: 10.1016/j.chbah.2025.100121.

27. X. Ochoa, X. Huang, and Y. Shao. “Exploring the potential of generative AI to support non-experts in learning analytics practice”. In: *Journal of Learning Analytics* 12.1 (2025), pp. 65–90. DOI: 10.18608/jla.2025.8615.
28. A. Chen et al. “Can theory-driven learning analytics dashboard enhance human-AI collaboration in writing learning? Insights from an empirical experiment”. In: *The Internet and Higher Education* 68 (2026), p. 101054. DOI: 10.1016/j.iheduc.2025.101054.
29. Y. Shi et al. “Large language models in education: A systematic review of empirical applications, benefits, and challenges”. In: *Computers and Education: Artificial Intelligence* 10 (2026), p. 100529. DOI: 10.1016/j.caeai.2025.100529.
30. L. Urquhart and X. M. Ngo. “Changing EAP assessment practices in the age of generative artificial intelligence: The case of Scottish higher education institutions”. In: *Journal of English for Academic Purposes* 79 (2026), p. 101609. DOI: 10.1016/j.jeap.2025.101609.
31. D. Sun et al. “When generative AI meets Socratic method: Investigating programming learning dynamics through behaviours, interaction qualities and perceptions”. In: *Journal of Computer Assisted Learning* 42.2 (2026), e70210. DOI: 10.1002/jcal.70210.
32. Confucius. *The Confucian Analects*. Ed. by James Legge. Translated by James Legge, in The Chinese Classics, vol. 1, Book II, 2.15. 1861.

Open Access This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (http://creativecommons.org/licenses/by-nc/4.0/), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.

