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Hybrid intelligence and educational agency: Towards an ecology of human-AI collaboration

Inteligencia híbrida y agencia educativa: hacia una ecología de colaboración humano-IA

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ABSTRACT

The emergence of generative artificial intelligence has revived an enduring question in educational technology: Should artificial intelligence (AI) supplant teachers or support them? The evidence does not sustain either pole. This article advances hybrid intelligence, an integrated mode of human-AI collaboration in which agency, judgment, and accountability are shared rather than lodged in just one side, as a more useful lens for understanding AI in education. Using a theoretical and argumentative method, the paper defines the concept. It separates hybrid intelligence from adjacent ideas, including blended learning and educational AI, and links its philosophical lineage to extended mind theory, man-computer symbiosis, and actor-network theory. The article then examines three major conceptual frameworks: Molenaar's six-level automation model, Cukurova's AIED-HCD taxonomy, and Holstein, Aleven, and Rummel's hybrid adaptivity model. These are brought together in a five-level architecture for hybrid learning ecosystems: people and roles, hybrid space, data, models, and governance. In addition, it sketches three scenarios for the gradual incorporation of AI into university teaching, together with the nine persistent challenges (the "elephants in the room"). The discussion highlights shared patterns across the frameworks and the teaching competencies required for hybrid intelligence. The article ends by arguing that, in education, hybrid intelligence can realise its potential only through a human-centred orientation: technology must adapt to education, not education to the technology.

Palabras clave

Inteligencia híbrida; Colaboración humano-IA; Agencia educativa; Ecosistemas de aprendizaje híbridos; Inteligencia artificial en educación

RESUMEN

La llegada de la inteligencia artificial generativa ha reabierto una discusión que lleva tiempo viva en la tecnología educativa: ¿acabarán las máquinas sustituyendo al profesorado o se limitarán a apoyarlo? La evidencia no respalda ninguna de esas dos posiciones. En este artículo se plantea la inteligencia híbrida como el encuadre más útil para pensar la inteligencia artificial (IA) en la educación: una cooperación simbiótica entre personas e IA en la que la agencia, la decisión y la responsabilidad se reparten en vez de quedar en manos de una sola parte. Desde una perspectiva teórica y argumentativa, el texto acota el concepto y lo separa de ideas afines como el *blended learning* o la IA educativa, al tiempo que sigue sus fundamentos filosóficos en la tesis de la mente extendida, la simbiosis hombre-computadora y la teoría del actor-red. A continuación, examina tres marcos conceptuales de referencia (el modelo de seis niveles de automatización de Molenaar, la taxonomía AIED-HCD de Cukurova y el marco de adaptatividad híbrida de Holstein, Aleven y Rummel) y los articula en una arquitectura de cinco niveles para los ecosistemas de aprendizaje híbridos: personas y roles, espacio híbrido, datos, modelos y gobernanza. Además, presenta tres escenarios para incorporar progresivamente la IA en la docencia universitaria, junto con los nueve desafíos persistentes: los "elefantes en la habitación". La discusión pone de relieve las convergencias entre estos marcos y las competencias docentes que la inteligencia híbrida demanda. El artículo concluye que la inteligencia híbrida solo puede materializar su promesa en la educación si adopta un enfoque centrado en el ser humano: la tecnología debe ajustarse a la educación, y no al contrario.

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1. Introduction

The rise of artificial intelligence (AI) in education, particularly since the emergence of generative AI (GenAI) (García-Peñalvo & Vázquez-Ingelmo, 2023; Jovanović & Campbell, 2022), has sharpened one of the most pressing debates in contemporary educational technology: how to integrate increasingly capable intelligent systems without reducing pedagogical complexity to automatable processes. GenAI itself, together with learning analytics (Drăgoi et al., 2026) and adaptive systems (Čep et al., 2026), has reignited a long-standing tension between two extreme positions. On one side stand narratives that project an ever-growing automation of teaching, built on virtual tutors, recommendation systems, automated grading, and algorithmic personalization of learning pathways (Topali et al., 2025; Zawacki-Richter et al., 2019). On the other side stand warnings about the risk of dehumanisation (Selwyn, 2022), of surveillance and the erosion of teacher autonomy (Williamson et al., 2023), of the weakening of academic authorship (Kaebnick et al., 2023), and of the subordination of education to technology (Bulathwela et al., 2024), which could give rise to an apocalyptic vision of machines replacing teachers (Rahm, 2023).

Neither of these extreme positions is productive, nor do they hold up against the available scientific evidence. As Molenaar (2022) points out, the replacement perspective, according to which AI will eventually supplant teachers, is not only a persistent myth (Alier-Forment et al., 2026; García-Peñalvo, 2024b) but also runs counter to the real possibilities of a synergistic integration between human and artificial capabilities.

Against this polarisation, another reading is beginning to take hold in academic circles. The question is no longer whether to choose between human presence and automation, but rather how agency, decision-making capacity, and responsibility are distributed across environments where teachers, students, platforms, analytics, conversational assistants, and regulatory frameworks coexist. This is the augmentation perspective, which conceives of AI not as a substitute for human beings but as an amplifier of their capabilities, an advanced instrument whose usefulness depends on how it is orchestrated within the educational ecosystem. The orchestra metaphor conveys that value lies not in a "perfect soloist" but in the coordinated composition of different actors, one in which teachers retain pedagogical direction while technology expands the possibilities without appropriating the educational meaning of the process.

This perspective has deep roots in the history of computing. As early as 1960, Licklider (1960) framed man-computer symbiosis as a cooperative partnership in which both parties contribute their specific strengths. Decades later, the concept of hybrid intelligence formalised this intuition, defining it as "the ability to achieve complex goals by combining human and artificial intelligence, thereby reaching superior results to those each of them could have accomplished separately, and continuously improve by learning from each other" (Dellermann et al., 2019, p. 640).

This article adopts the hybrid intelligence perspective as a framework for analysing how collaboration between humans and AI can be orchestrated in educational settings. The term makes it possible to address a reality more complex than the simple juxtaposition of face-to-face and online teaching, or of human decisions and automated assistance. The hybrid establishes a synergy between heterogeneous capabilities. Human intelligence contributes contextual judgement, empathy, creativity, ethical deliberation and situated understanding. Artificial intelligence contributes computational speed, the capacity to process large volumes of data, response generation and support for personalisation. The question is how to combine the two without blurring human responsibility, reducing learning to what is easily measurable, or turning the technological infrastructure into an opaque mechanism of control.

The general aim of this paper is to develop a theoretical and argumentative proposal on hybrid intelligence in education. It does not present original empirical research or quantitative results, but rather an analytical synthesis and a conceptual elaboration. In this sense, it is a theoretical, essayistic text, oriented towards clarifying concepts, organising debates and proposing a roadmap for the responsible integration of AI in higher education.

More specifically, the paper pursues four concrete objectives. First, to delimit the concept of hybrid intelligence and distinguish it from other related notions, such as blended learning (Graham, 2006) or educational AI (Ouyang & Jiao, 2021). Second, to review the conceptual frameworks that allow human-AI collaboration in education to be thought through, especially those related to the augmentation perspective, hybrid adaptivity and extended cognition. Third, to analyse the risks and tensions that emerge when AI is incorporated into learning ecosystems: opacity, bias, surveillance, loss of agency, data overdetermination and disconnection from pedagogical aims. Fourth, to propose operational criteria and gradual adoption scenarios that guide a safe, ethical and pedagogically meaningful implementation.

This approach is especially pertinent at the moment, when the emergence of GenAI models, particularly large language models (LLMs) (Yang et al., 2024), has intensified both expectations and fears surrounding AI in education. The temptation to adopt these tools uncritically or to reject them outright (García-Peñalvo, 2023) reproduces the same dichotomous logic that the hybrid intelligence perspective sets out to overcome. What is required instead is a nuanced approach that recognises the transformative potential of these technologies while articulating the control, oversight, and evaluation mechanisms necessary for their responsible integration (García-Peñalvo, 2024a).

The article is structured as follows. First, the theoretical framework underpinning hybrid intelligence is established, including its philosophical roots and operational definitions. Next, the main conceptual frameworks for hybrid intelligence in education are presented and analysed. The notion of a hybrid learning ecosystem is then developed, and the scenarios for gradual integration are described. The ethical, methodological and regulatory challenges are then examined. Finally, the implications of this perspective are discussed, and the conclusions are presented.

2. Fundamentals of hybrid intelligence

2.1. From blended learning to hybrid intelligence

The notion of the hybrid has traditionally been associated with the combination of face-to-face and online modalities in education. In this sense, so-called *blended learning* has been interpreted as a modality that harnesses the strengths of face-to-face interaction and digital flexibility. That reading remains relevant, not least because it made it possible to rethink the temporal and spatial conditions of teaching and opened the way towards more flexible, personalised and participatory designs. However, the recent expansion of AI calls for broadening the meaning of the hybrid, which can no longer be reduced to the sum of face-to-face and virtual instruction.

In contemporary learning ecosystems (Molina-Carmona et al., 2017), hybridisation also encompasses interactions among people, data, automated systems, and accountability frameworks. For this reason, the shift from hybrid education to hybrid intelligence does not simply consist of adding intelligent tools to a *blended* environment, but rather of recognising that learning and teaching are increasingly configured as socio-technical processes in which human and artificial capabilities are combined.

Along these lines, Dellermann et al.'s (2019) definition of hybrid intelligence includes two particularly relevant elements. The first is that AI ceases to be treated as invisible infrastructure or mere functional support and becomes an active component of the cognitive and organisational process. The second is that the evaluation criterion is no longer mere efficiency but the quality of the combination: what matters is how tasks, decisions, controls and possibilities for intervention are distributed.

The hybrid is, therefore, a synergy, a kind of "1 + 1 = 3", that is, a multiplication of capabilities rather than a linear sum, which helps in thinking beyond simplifying dualisms: human versus machine, natural versus artificial, mind versus tool. From this standpoint, hybridisation would not be a loss of humanity but a way of reorganising capabilities into a more complex assemblage.

2.2. From the logic of replacement to the augmentation perspective

The relationship between artificial intelligence and education has been marked for decades by what Molenaar (2022) calls the replacement perspective, that is, the belief that advances in AI will inevitably lead to teachers being replaced by automated systems. This view, periodically fuelled by the media and by a certain techno-optimist rhetoric, has generated both excessive expectations and legitimate resistance among education professionals.

Empirical research, however, offers a very different picture. Studies on the use of adaptive learning technologies in real classrooms show that AI works better when combined with teacher intervention, not when it replaces it. Holstein et al. (2018; 2019) showed that augmented-reality dashboards for teachers, based on analytics from intelligent tutoring systems, improved classroom equity by giving teachers additional information about which students needed help. This contribution supports the idea that AI can extend teachers' perceptual capabilities, allowing them to detect needs that would otherwise go unnoticed.

The augmentation perspective is not simply an intermediate position between total replacement and outright rejection. It constitutes a paradigm shift that recognises the fundamental complementarity between human and artificial capabilities. While AI excels at processing large volumes of data, identifying patterns, and consistently executing repetitive tasks, human beings contribute contextual understanding, empathy, ethical judgement, creativity and the ability to adapt to unforeseen situations (Akata et al., 2020). In education, this translates into a division of functions in which AI can take on tasks such as detecting each student's level of knowledge, diagnosing learning difficulties or recommending resources, while teachers concentrate on personalised tutoring, motivation, conflict resolution and the holistic development of learners.

2.3. Scope of hybrid intelligence

As noted above, the concept of hybrid intelligence was formalised by Dellermann et al. (2019). Their definition distinguishes three essential aspects. First, that it is an emergent capability, not a mere sum of parts; second, that it is oriented towards complex goals that neither form of intelligence could effectively address on its own; and third, that the outcome of the combination is qualitatively superior to that of each component separately.

In the educational context, hybrid intelligence implies that AI systems and human agents (teachers, students, administrators) collaborate reciprocally and dynamically. This is not a matter of AI simply assisting the teacher in a one-directional way, but of both forms of intelligence informing and reinforcing one another. As Molenaar (2022) emphasises, bidirectional interaction is essential. Teachers contribute contextual information, classroom observations and professional judgement that improve the detection and diagnosis carried out by AI, while AI provides processed data, identified patterns and recommendations that extend teachers' capacity for action.

Akata et al. (2020) proposed a research agenda for hybrid intelligence that identifies four fundamental properties that hybrid systems must exhibit: collaborative, adaptive, responsive, and explainable. These properties take on particular importance in education, where trust, transparency and accountability are unavoidable ethical requirements. A hybrid intelligence system in education must be able to explain its recommendations, adapt to diverse contexts, respond to the changing needs of students and teachers, and facilitate genuine collaboration among all the actors involved.

2.4. Philosophical foundations

Hybrid intelligence in education does not emerge in a conceptual vacuum; rather, it draws on various philosophical traditions that have explored the relationship between human beings and technology. Four perspectives are particularly relevant. First, Clark and Chalmers's (1998) extended mind thesis proposes that cognitive processes are not confined to the brain but can extend into tools and artefacts in the environment. Applied to educational AI, this perspective suggests that intelligent systems can function as genuine extensions of students' and teachers' cognition, rather than as merely external instruments.

Second, Licklider's (1960) vision of man-computer symbiosis anticipated a cooperative relationship in which humans and machines would work intimately together, each contributing what it does best. Licklider distinguished between formulative and creative tasks, which are proper to human beings, and routine and computational tasks, better suited to the machine. This symbiotic metaphor remains valid for conceptualising educational hybrid intelligence, as it captures the idea that the optimal relationship between humans and AI is not hierarchical but mutualistic.

Third, the figure of the cyborg proposed by Haraway (1991), or that of the digital centaur proposed by Marina (2020), blurs the boundaries between the human and the technological, inviting a rethinking of identities and capabilities in hybrid terms. In the contemporary educational context, where students and teachers interact daily with AI systems, the cyborg metaphor takes on particular resonance: the learning subject is no longer a purely biological agent but a hybrid system that integrates its own cognitive capabilities with those provided by intelligent digital tools.

Finally, Latour's (2005) actor-network theory offers a framework for understanding how human and non-human agents (including AI systems) are articulated into networks of distributed action, which is especially pertinent for conceptualising hybrid learning ecosystems. From this perspective, educational agency does not reside exclusively in teachers or in technology but emerges from the interaction among multiple human and non-human actors that make up the classroom's socio-technical network.

3. Conceptual frameworks for hybrid intelligence in education

Various authors have proposed conceptual frameworks to structure our understanding of how humans and AI can collaborate in educational settings. This section analyses the three most influential frameworks, which offer complementary perspectives on this question.

3.1. The six-level automation model

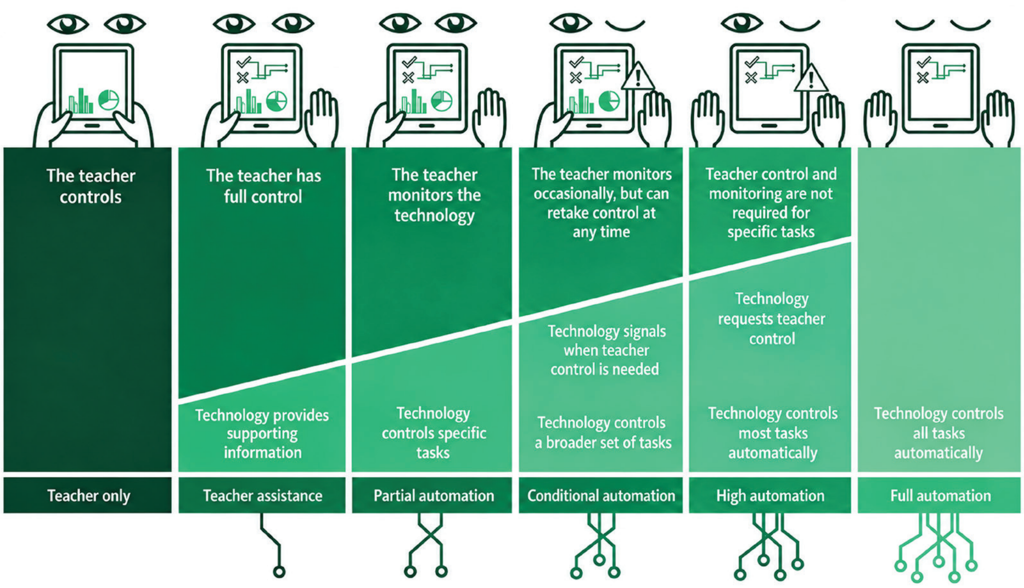
Molenaar (2022) developed a six-level automation model (see Figure 1) that describes the spectrum of possible configurations of control division between humans and AI in educational settings. This model is based on the sense-diagnose-act framework, which conceptualises the functioning of AI in education in three phases: sensing relevant data about the learning process, diagnosing the student's state, needs and difficulties, and acting through appropriate pedagogical interventions.

At the first level, called teacher only, the teacher controls the educational process entirely, with no AI intervention whatsoever. At the second level, teacher assistance, AI senses and diagnoses relevant data but does not act directly; instead, it communicates useful information to the teacher through *dashboards* or reports. The teacher retains full control over pedagogical actions but has additional information available to inform their decisions. Research has shown that this level can have significant effects; information *dashboards* for teachers change their professional routines and pedagogical actions (Knoop-van Campen & Molenaar, 2020; van Leeuwen et al., 2021).

The third level corresponds to partial automation, in which AI takes control of specific tasks, such as step, task or curriculum adaptivity, while the teacher retains overall supervision. At the fourth level, conditional automation, AI also takes control of monitoring, sensing and diagnosis, and acts on a broader set of tasks, although the teacher can resume control at any time. The fifth level, high automation, means that AI automates most tasks and can ask the teacher to intervene in complicated cases. Finally, the sixth level, full automation, entails the absence of human oversight, a highly unlikely scenario in formal education and one that raises serious ethical questions.

The conclusion regarding this model is that in formal educational settings, conditional automation is probably the optimal way to combine human and artificial intelligence, since it guarantees sufficient human control while still harnessing AI's capabilities. In specific fields, such as medicine (Topol, 2019), it is unlikely that developments will move beyond conditional automation without removing humans from the process. There is a real risk that humans will end up not only on the loop but also out of the loop, which calls for ongoing dialogue among education professionals, researchers and developers to keep humans in the loop and to evaluate the augmentation perspective. This position aligns with the augmented perspective and underscores the importance of keeping human beings as the central agents of the educational process.

Figure 1. Six-level automation model for personalised learning. Adapted from (Molenaar, 2022)



3.2. The AIED-HCD framework: three conceptualisations of AI

Cukurova (2025) proposes the AIED-HCD framework (*Artificial Intelligence in Education for Human-Centred Design*), which offers a taxonomy of three fundamental conceptualisations of how AI can relate to human cognition in education.

The first conceptualisation is AI as the externalisation of human cognition. In this perspective, AI is designed to replicate specific human cognitive abilities, such as assessing written work or grading exams. The aim is to automate tasks normally performed by the teacher, freeing them up for higher-value activities. Classic intelligent tutoring systems (Corbett et al., 1997) and automated assessment systems (García-Peñalvo et al., 2026) are representative examples of this conceptualisation. Although useful, excessive reliance on this perspective risks reducing learning to whatever AI can measure and evaluate, impoverishing the educational experience (Knox et al., 2020).

The second conceptualisation presents AI as the internalisation of human cognition. Here, AI is conceived as a tool that, when used by the student, transforms and enriches their cognitive processes. Intelligent *scaffolding* systems that guide students through problem-solving (Jang et al., 2026), writing assistants that stimulate metacognitive reflection (El Hosayny et al., 2026; Zhang & Liang, 2026), and simulation environments that allow abstract concepts to be explored experientially (Moshaver & Mehdizadeh, 2026) exemplify this perspective. The risk lies in the fact that, if AI systems carry out part of the cognitive work that the student should be doing, they can undermine learning rather than enhance it (Bastani et al., 2025), or give rise to so-called *metacognitive laziness*, whereby not only the task but also the supervision of the learning process itself is delegated to AI, with negative effects on self-regulation (Fan et al., 2025).

The third conceptualisation would be the one most closely aligned with the hybrid intelligence view. Here, AI would act as an extension of human cognition. Inspired by Clark and Chalmers's (1998) extended mind thesis, this perspective views AI as an extension of human cognitive capabilities, enabling students and teachers to achieve goals that would not be possible without the combination of both forms of intelligence. Learning analytics systems that make hidden patterns in educational data visible (Prinsloo et al., 2024) and generative AI tools that enable exploration of expanded creative spaces (Creely & Blannin, 2025) illustrate this approach. The key point is that AI should not replace or replicate human cognition but rather extend it in directions that human beings alone could not explore (Cukurova, 2025).

3.3. The hybrid adaptivity framework

Holstein, Aleven and Rummel (2020) propose a conceptual framework for human-AI hybrid adaptivity in education that analyses how adaptive functions can be shared between educational AI systems and human facilitators (teachers, tutors, peers). Their starting point is the empirical observation that, in practice, adaptivity in classrooms is not an exclusive property of AI systems but is jointly enacted by artificial and human agents. For example, in primary-education classrooms that use intelligent tutoring *software*, the sequence of activities received by students results from a combination of algorithmic selection and the teacher's dynamic decisions, who can selectively override the system's recommendations.

This framework is structured around five dimensions: goals and objectives, perceptual capabilities, action space, decision policies, and granularity/temporality. For each dimension, the framework explores how humans and AI systems can mutually enhance one another's capabilities. It identifies four categories of augmentation: goal augmentation (each agent's objectives inform and enrich those of the other), perceptual augmentation (each agent extends the other's sensing and diagnostic capabilities), action augmentation (each agent expands the repertoire of interventions available to the other), and decision augmentation (each agent improves the quality of the other's decisions). Within each category, a distinction is drawn between performance augmentation (immediate improvements in an agent's capabilities) and co-learning (in which both agents improve their capabilities over time).

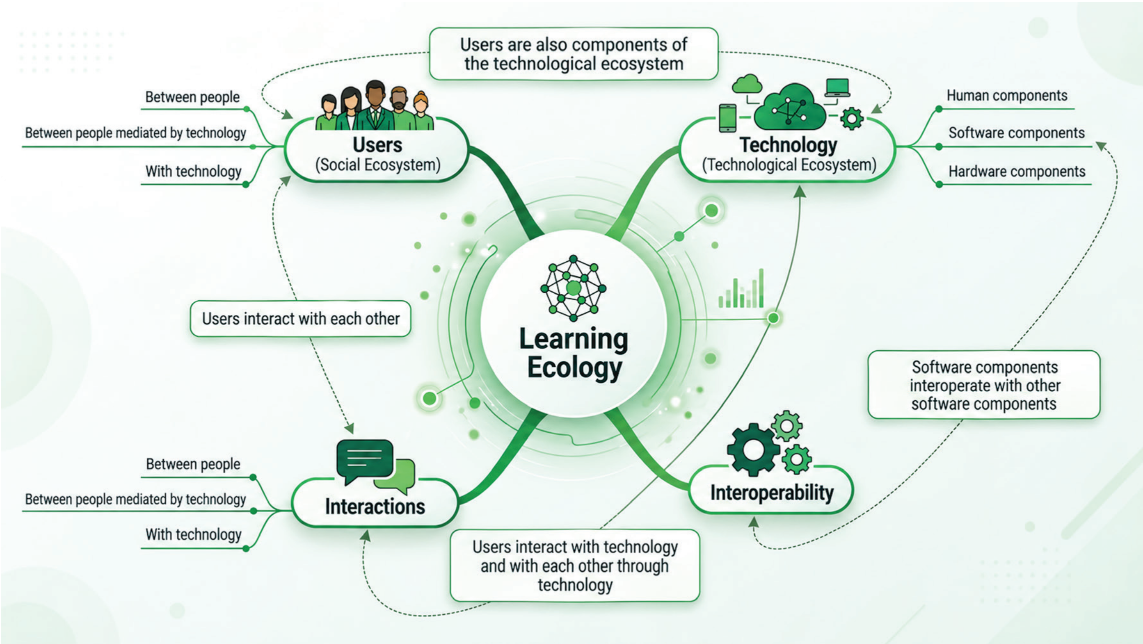
A significant contribution is the identification of potential tensions in goal augmentation. The objectives built into educational AI systems do not always coincide with those of teachers in real-world contexts. For example, many intelligent tutoring systems implement mastery-based domain policies, yet teachers often need to balance personalisation against the pressure to keep up with curriculum pacing. This tension underscores the need for hybrid intelligence systems capable of negotiating and reconciling the objectives of their multiple agents.

4. Hybrid learning ecosystems

4.1. Conceptualisation and components

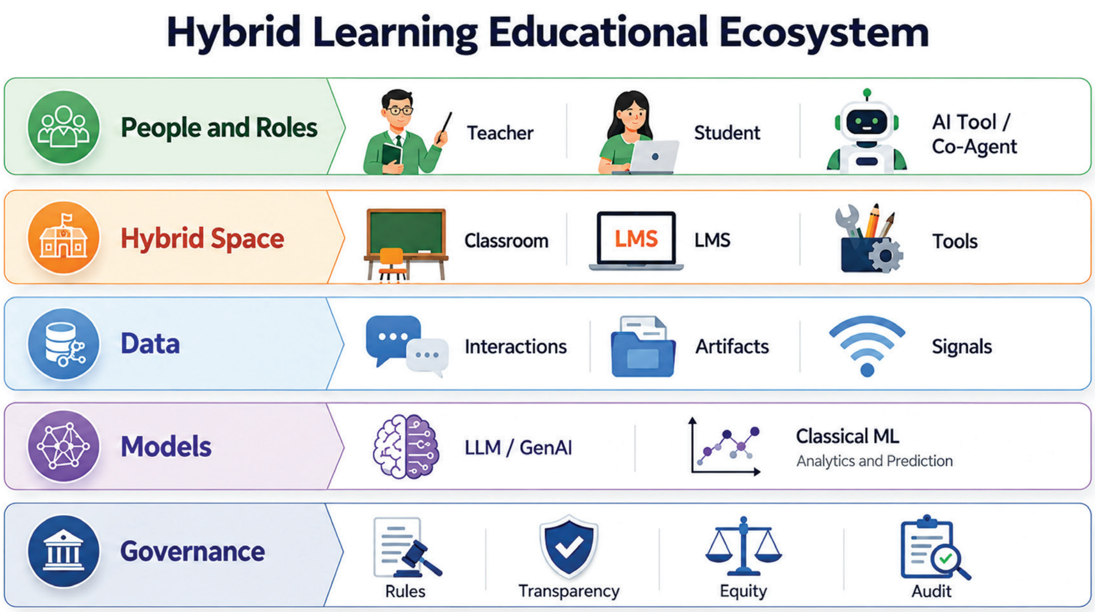
The effective integration of hybrid intelligence in education requires going beyond the mere implementation of isolated tools and thinking in terms of ecosystems. A hybrid learning ecosystem can be defined as an integrated educational environment that combines face-to-face and virtual spaces, multimodal data, human agents (teachers, students, administrators) and artificial agents (AI systems), articulated under principles of accountability, transparency and equity in order to enhance teaching-learning processes, and which evolves from the concept of the learning ecology shown in Figure 2 (García-Peñalvo, 2018).

Figure 2. Learning ecology. Adapted from (García-Peñalvo, 2018)



The fundamental components of a hybrid learning ecosystem (see Figure 3) follow a five-level architecture.

Figure 3. Architecture of a hybrid learning educational ecosystem. Source: Author's own elaboration



The first level consists of people and roles: the teacher, the student and AI, which, within this framework, functions less as a simple tool and more as a co-agent with its own capabilities and limitations. Molenaar (2022) stresses that these actors do not operate in isolation. Their relationship must be considered from a quadruple-helix perspective (Leydesdorff, 2012), which also involves researchers, policymakers, and technology companies in the design of the ecosystem. No decision about these systems is purely technical. It always has pedagogical, ethical, and economic dimensions that require a multi-actor outlook.

The second level is the hybrid space itself, that is, the interaction spaces, which comprise both face-to-face environments (classrooms, laboratories, collaborative workspaces) and virtual ones (learning platforms, communication environments, AI tools). Seamless integration of the two types of spaces is essential for hybrid intelligence to operate effectively.

The third level corresponds to data, the informational substrate of the entire ecosystem. Molenaar (2022) distinguishes three types: interactions, that is, usage *logs* and communication recorded in the LMS (*Learning Management System*); artefacts produced by teachers and students, such as assignments, assessments and materials; and signals, coming from sources such as eye-tracking, movement or physiological data. The more of these data streams are combined, the greater the system's capacity to detect patterns and diagnose learning difficulties.

The fourth level corresponds to the models that process this data. A distinction should be drawn between large language models and other forms of generative AI, geared towards producing content and feedback, and classic machine learning, centred on analytics and prediction tasks such as the early detection of dropout risk. Each type of model performs a distinct function within the ecosystem, and the two are complementary.

The fifth and final level is governance: the rules, transparency, equity, and auditing that ensure everything above functions within acceptable ethical and legal limits. Without this level, neither the personalisation of learning nor the use of the data collected can be considered legitimate, however sophisticated the underlying models may be.

The notion of a hybrid learning ecosystem differs from earlier concepts such as blended learning in one fundamental respect: it is not limited to combining face-to-face and virtual modalities but explicitly integrates artificial intelligence as an active agent within the ecosystem. Whereas traditional blended learning focuses on combining learning spaces and times, the hybrid ecosystem additionally incorporates combining intelligences (human and artificial) as its organising axis. This conceptual expansion has practical consequences, since it requires rethinking not only the logistics of learning (where and when learning takes place) but also the epistemology of learning (how knowledge is generated, validated, and applied when humans and AI collaborate).

4.2. Generative AI in the hybrid ecosystem

The emergence of GenAI models, particularly LLMs, has radically transformed the role of AI in education. These systems introduce unprecedented capabilities (text generation, code, multimedia content, conversational interaction, and so on), which significantly expand the action space of hybrid ecosystems. At the same time, they raise new challenges related to the veracity of information, academic integrity, linguistic equity and technological dependence (García-Peñalvo, 2024a).

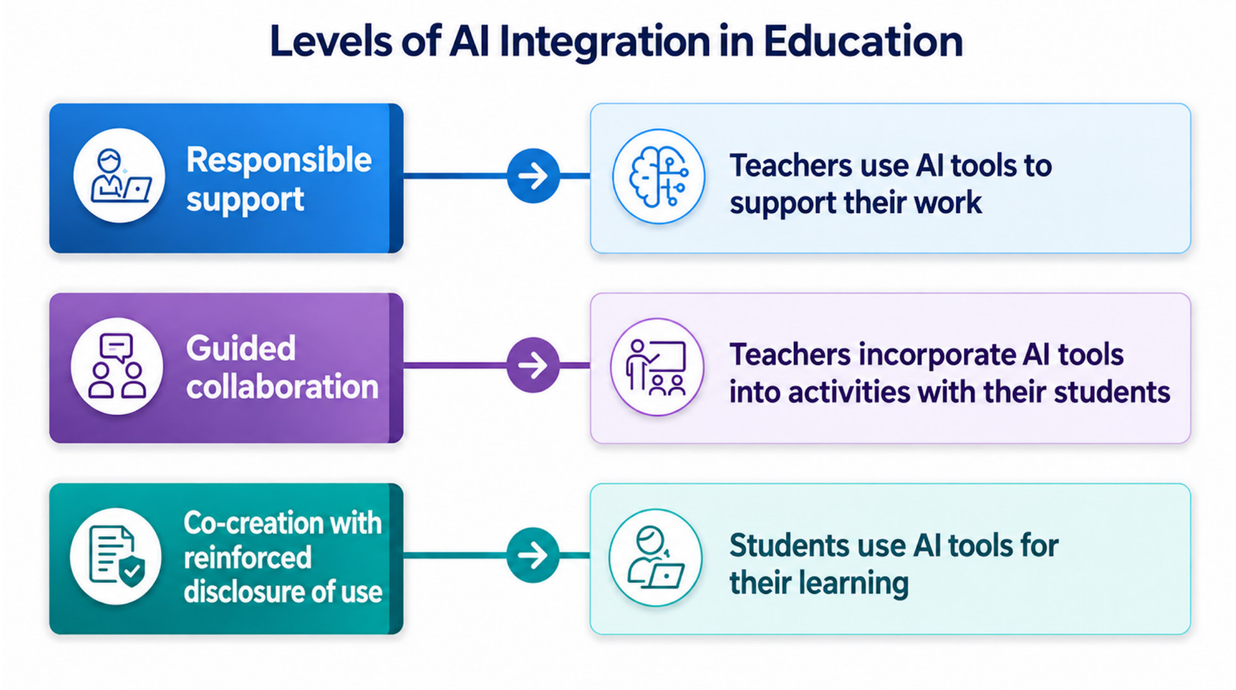
From the perspective of hybrid intelligence, GenAI presents both opportunities and risks. Among the opportunities, one that stands out is the possibility of personalising learning at a scale previously unattainable; LLMs can function as conversational tutors that adapt to each student's level, style and needs (Pardos & Bhandari, 2024). They can also act as cognitive scaffolding tools (Kudina et al., 2025) that help students structure their thinking, explore alternative perspectives or overcome creative blocks. However, as both Cukurova (2025) and Hooshyar et al. (2025) warn, there is a real risk that these systems will perform students' cognitive work, thereby distorting authentic learning.

In this context, Hooshyar et al. (2025) point out that GenAI has disproportionately dominated recent educational discourse, overshadowing other families of AI (expert systems, classic machine learning, deep learning, neuro-symbolic AI) that have different purposes, strengths and limitations. The tendency to equate AI in education with LLMs in education impoverishes understanding of the field and makes it harder to select the most suitable tools for each pedagogical objective. A mature hybrid ecosystem should integrate multiple types of AI, each contributing its specific capabilities according to the needs of the context.

4.3. Three scenarios for the gradual integration of AI in university teaching

García-Peñalvo (2025) proposes three scenarios that describe a gradient for integrating AI into university teaching, allowing its use to be scaled up as safeguards and trust in the technology are established (see Figure 4).

Figure 4. Scenarios for integrating AI into teaching. Based on (García-Peñalvo, 2025)



These scenarios are neither mutually exclusive nor necessarily sequential; rather, they represent increasing levels of AI autonomy and, consequently, increasing demands on control and oversight mechanisms.

The first scenario, responsible assistance (low risk and low AI autonomy), envisages using AI as a tool for consultation and basic assistance. Teachers may use AI within the teaching cycle, but assessment rests entirely on human work. A policy of full transparency is established: teachers must declare when and how they have used AI. This scenario minimises risk by maintaining high transparency and strong domain knowledge.

The second scenario, guided collaboration (medium risk, moderate AI autonomy), enables deeper, more sustained interaction between students and AI. AI is used, but always under the active supervision of the teacher, who has defined which tools may be used, how and when. Emphasis is placed on the traceability of AI's contribution; it must be clear which parts were done by AI and which by the student. Teachers supervise interactions, train students in the appropriate use of *prompts*, and verify that substantial post-editing has occurred. In this way, AI becomes a collaborator, with students practising *AI literacy* skills while teachers ensure the process aligns with the learning objectives.

The third scenario, supervised co-creation (higher risk, high AI autonomy), corresponds to the most advanced and autonomous use of AI, in which students and AI co-create solutions or artefacts. AI takes on a more proactive role, even generating content that goes directly into final products, always under exhaustive controls, given the greater potential impact. Robust evidence and complete audit mechanisms are required: detailed logs of *prompts* and responses, successive versions of the work, fact-checking and verification of external citations, analysis of possible biases, and human or peer review of all machine-generated parts before final assessment. The idea is that, even though AI plays a broad role, nothing it produces should go unnoticed or unvalidated in the final product.

These three scenarios reflect a gradient of integration that allows the use of AI to be scaled up as safeguards and trust in the technology are established. The first scenario emphasises risk minimisation, maintaining high transparency, and placing AI use on the teacher's side; the second promotes traceable collaboration with training in human judgement; the third acknowledges autonomous use by students, full co-creation, with a high risk that demands solid evidence and auditing of the entire process.

4.4. Tools and experiences

Bringing hybrid learning ecosystems to life requires concrete tools that facilitate the integration of AI into existing learning environments. A relevant example is LAMB (*Learning Assistant Manager and Builder*) (Alier et al., 2025), which enables the creation of AI assistants integrated into learning management systems. LAMB enables teachers to design, configure, and deploy AI assistants tailored to their specific pedagogical needs, while retaining control over the system's behaviour and protecting the data of the agents involved.

This type of tool represents an important step towards operationalising hybrid intelligence in real educational settings, since it addresses two frequent obstacles. On one hand, teachers' lack of control over AI tools; on the other, the lack of integration between AI systems and institutional educational platforms. By allowing teachers to configure AI assistants within the institutional LMS, LAMB embodies the augmentation perspective by placing technology at the service of the teacher's pedagogical decisions, rather than imposing a technological logic alien to the educational context, which is entirely consistent with the principles of the Safe AI in Education Manifesto (Alier et al., 2024; García-Peñalvo et al., 2024).

5. Challenges and outstanding issues

5.1. The nine elephants in the room

Hooshyar et al. (2025) identify nine persistent critical problems in the field of AI in education that, despite being widely recognised, remain unresolved and act as the *elephants in the room*. These challenges can be grouped into three broad categories that reveal the field's structural weaknesses.

The first category groups together the problems of disconnection from human and pedagogical reality. The first problem is the lack of clarity about what AI actually means for education, since the purposes, strengths, and limitations of different families of AI are often ignored, and educational AI is often equated with large language models (Shiri, 2024). The second problem is excessive generalisation; recommendations tend to be global when they should be localised and specific to each student (Laak & Aru, 2025). The third is the widespread neglect of essential learning processes (such as motivation, emotion, and metacognition) in AI-driven student models (Banihashem et al., 2025), which tend to reduce the learner to their academic outcomes alone.

The second category covers the problems of methodological fragility. The fourth problem is the limited integration of domain knowledge and the lack of participation by educational actors in the design and development of AI systems (Alfredo et al., 2024). The fifth is the continued use of non-sequential machine learning models on temporal educational data, which fail to capture the dynamics and dependencies critical to understanding real learning progressions (Lee et al., 2025). The sixth is the inappropriate use of non-sequential metrics to evaluate sequential or temporal models (Pelánek, 2015).

The third category brings together the problems of a crisis of trust and transparency. The seventh problem is the use of unreliable explainable AI methods to explain black-box models, even when interpretable alternatives with comparable performance are available (Rudin, 2019). The eighth is disregard for ethical guidelines when addressing data inconsistencies during model training (Baker & Hawn, 2022). The ninth is the use of *mainstream* AI methods for pattern discovery and learning analytics without systematic evaluation (Hooshyar et al., 2020), which can lead to unreliable conclusions.

Hooshyar et al. (2025) propose hybrid AI methods, specifically neuro-symbolic AI, to address these challenges by combining symbolic reasoning with neural learning to achieve systems that are more transparent, interpretable, and aligned with educational domain knowledge.

5.2. Regulatory and ethical framework

The integration of hybrid intelligence in education cannot be separated from a regulatory and ethical framework. At the international level, UNESCO (2019) has established guidelines on the use of AI in education that emphasise equity, transparency and data protection. In the European context, the European Union's AI Act (European Parliament & The Council of the European Union, 2024) classifies education as a high-risk domain for AI applications, imposing specific requirements for transparency, explainability and human oversight that align with the hybrid intelligence perspective.

Specifically in education, the Safe AI in Education Manifesto (Alier et al., 2024; García-Peñalvo et al., 2024) articulates seven principles for the safe and responsible integration of AI in educational contexts. These principles include human oversight, data privacy, equity and non-discrimination, transparency, security, accountability and inclusion. By requiring explainability, human oversight, and risk assessment, the current regulatory framework reinforces the need to adopt a hybrid intelligence perspective rather than full-automation models that do not allow human participation in decision-making.

5.3. Teaching competencies for hybrid intelligence

The effective implementation of hybrid learning ecosystems requires a profound transformation of teaching competencies. Teachers need to develop what could be called a hybrid competency that integrates at least four interrelated dimensions.

First, *AI literacy*: a basic understanding of how AI systems work, what their capabilities and limitations are, and how to critically interpret their outputs. Without this understanding, teachers cannot exercise the informed oversight that hybrid intelligence models require.

Second, hybrid design competency: the ability to design learning experiences that coherently integrate human and artificial contributions, assigning each agent the tasks for which it is best suited.

Third, ethical and critical competency: the ability to assess the ethical implications of using AI in the classroom, detect biases, protect student privacy and ensure equity in access and outcomes. Almusaed et al. (2023) emphasise that teachers are the day-to-day guarantors of ethical implementation and must be trained in AI-related safety issues, be familiar with their institution's data protection policies, and be able to detect and report possible biases or failures in the tools.

Finally, a mindset of collaboration with technology: teachers must adopt an attitude that is open to working with AI systems, neither distrustful nor uncritically accepting, cultivating a teamwork attitude towards machines that combines confidence in delegating certain tasks with constant verification and feedback.

Developing these competencies requires significant institutional support, including ongoing training, technical-pedagogical mentoring, and communities of practice where teachers can share experiences with the use of AI in the classroom.

6. Discussion

The integrated analysis of the conceptual frameworks presented (Cukurova, 2025; Holstein et al., 2020; Molenaar, 2022), together with the scenarios for gradual integration (García-Peñalvo, 2025) and the identification of persistent challenges (Hooshyar et al., 2025), allows for several interesting reflections that help consolidate the concept of hybrid intelligence.

First, there is significant convergence among the frameworks analysed on the idea that the integration of AI in education should be conceived as a continuum of person-machine collaboration, rather than a binary choice between automation and traditional education. Molenaar's (2022) six levels, Cukurova's (2025) three conceptualisations, Holstein et al.'s (2020) four categories of augmentation, García-Peñalvo's (2025) three scenarios, and the persistent challenges identified by Hooshyar et al. (2025) each, from different angles, attempt to map this continuum and identify the optimal configurations for each context. This convergence suggests that the field is maturing towards a theoretical consensus around the hybrid intelligence paradigm, progressively overcoming (perhaps more slowly than would be desirable) the polarised visions of the past.

Second, the frameworks analysed share a concern about the risks of excessive or inappropriate automation. Molenaar (2022) warns of the risk that humans will end up "out of the loop" in highly automated systems. Cukurova (2025) warns that AI may undermine learning by taking over students' cognitive work. Holstein et al. (2020) point to tensions between the objectives of AI systems and those of teachers. Hooshyar et al. (2025) document nine critical problems that threaten the reliability and fairness of current systems. These convergent warnings reinforce the need to adopt hybrid intelligence not as a mere slogan but as an operational commitment to human oversight, transparency and accountability.

Third, it is significant that all the frameworks analysed underscore the importance of teachers' active participation, not only as users of AI but also as agents who inform, configure and evaluate hybrid systems. Molenaar's (2022) quadruple-helix perspective, the bidirectional interaction proposed by the hybrid adaptivity framework (Holstein et al., 2020), and the oversight and traceability mechanisms in García-Peñalvo's (2025) scenarios all agree that teachers play a central and irreplaceable role in the hybrid ecosystem. This has direct implications for teacher training, which needs to develop specific competencies for collaborating with AI systems, not only technical skills but also critical capacity, AI literacy and competencies for the ethical evaluation of educational technologies (UNESCO, 2024).

Nevertheless, several limitations of the current state of the field must be acknowledged. First, most of the conceptual frameworks analysed have been developed recently and still lack broad empirical validation across diverse educational contexts. Hybrid learning ecosystems, as conceptualised here, remain to a large extent a theoretical aspiration rather than a consolidated reality. Second, the rapid evolution of technology, especially in GenAI, increases the risk that conceptual frameworks will become obsolete before they can be fully implemented and evaluated (Beckman et al., 2025). Third, there are significant challenges regarding equity. The digital divide can translate into a hybrid intelligence divide, related to the concept of the *AI-divide* coined by Carter et al. (2020), unless equitable access to technologies and to the training needed to use them effectively is guaranteed.

Another aspect that deserves attention is the relationship between hybrid intelligence and self-regulated learning. Molenaar (2022) pays particular attention to how hybrid systems can support students' development of metacognitive and self-regulation skills. However, she also warns of a critical risk: excessive offloading of regulatory functions onto AI can harm the development of the cognitive and metacognitive skills that a person needs to cultivate. If an adaptive system makes all the decisions about what to study, when and how, learners lose essential opportunities to develop their capacity to plan, monitor and evaluate their own learning. This tension between support and dependence is one of the subtlest challenges of hybrid intelligence in education (Achuthan, 2025).

Finally, the successful implementation of hybrid learning ecosystems requires a profound cultural shift within educational institutions. It is not enough to introduce AI tools; pedagogical processes, forms of assessment, institutional policies and organisational cultures must all be rethought. The European regulatory framework, with the AI Act and UNESCO's guidelines, provides a legal scaffolding that favours responsible adoption, but real transformation will depend on institutions' capacity to articulate clear pedagogical visions in which AI is integrated as a component at the service of well-defined educational objectives. In other words, higher education institutions need an AI governance strategy that is fully aligned with their broader technology governance strategy and translated into concrete policies that serve as a reference for their community (Molina-Carmona & García-Peñalvo, 2025).

7. Conclusions

Hybrid intelligence represents a promising paradigm for integrating artificial intelligence into education. In contrast to dichotomous visions that oscillate between total replacement and outright rejection, the hybrid perspective proposes a synergistic collaboration between humans and AI in which each party contributes its specific strengths to achieve results superior to what either could achieve alone.

The conceptual frameworks analysed in this article offer complementary theoretical tools for articulating this vision. Molenaar's (2022) six-level automation model provides a common language for describing the division of control between humans and AI and identifies conditional automation as the optimal level for formal educational contexts. Cukurova's (2025) AIED-HCD framework offers a taxonomy of how AI can relate to human cognition, highlighting cognitive extension as the perspective most closely aligned with hybrid intelligence. Holstein et al.'s (2020) hybrid adaptivity framework details how adaptive functions can be shared and complemented between human and artificial agents. García-Peñalvo's (2025) three scenarios translate these theoretical frameworks into practical strategies for the gradual integration of AI into university teaching.

However, the full realisation of hybrid intelligence in education is contingent on resolving significant challenges, ranging from a lack of conceptual clarity to methodological and ethical shortcomings, a reminder that there is still a long way to go in terms of reliability, transparency and equity. The current regulatory framework provides useful guidelines, but ultimate responsibility rests with educational institutions and education professionals to shape genuinely hybrid learning ecosystems.

Future lines of research should address, among other aspects, the empirical validation of the conceptual frameworks presented across diverse educational contexts, the development of instruments to measure the quality of human-AI collaboration in the classroom, the design of teacher training programmes specific to hybrid intelligence, and longitudinal studies of the effects of these ecosystems on deep learning and the development of transversal competencies. It is also necessary to investigate how different educational levels, from primary education (Estrada-Molina et al., 2025) to higher education (García-Peñalvo et al., 2026), require distinct configurations of hybrid intelligence, adapted to the cognitive capacities, digital maturity and formative goals specific to each stage.

Ultimately, the key to the success of hybrid intelligence in education lies in maintaining a human-centred approach: technology must adapt to education, not education to technology. This means empowering teachers and students with AI tools that remain under their control and understanding, embedding training in digital literacy and AI ethics at every level, and building learning ecosystems in which artificial intelligence can be orchestrated harmoniously with human intelligence, combining their respective strengths to achieve the shared goal of a higher-quality, inclusive, critical and sustainable education in the digital era.

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