Rethinking intelligence: A critical examination of the concept of “artificial intelligence”

Repensar la inteligencia: Una reconsideración crítica del concepto de “inteligencia artificial”

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Abstract
This article critically examines the use of the term “artificial intelligence” in education and argues that its widespread use can create conceptual and pedagogical confusion. Drawing on theoretical work by Pierre Lévy, Hubert Dreyfus, Sherry Turkle, and Kate Crawford, the article argues that systems currently described as “intelligent” do not think, understand, or possess intentionality. Rather, they operate through statistical pattern recognition based on data generated by human beings. The article analyzes the historical and philosophical origins of the concept of intelligence, as well as the evolution of the term “artificial intelligence,” to highlight the gap between what these technologies do and what the term implies. It also distinguishes among discriminative AI, generative AI, large language models, chatbots, and AI agents in order to avoid treating them as interchangeable concepts that involve different functions and pedagogical implications. In addition, the article questions terms such as “co-intelligence” and “co-creation,” arguing that they imply a problematic symmetry between humans and machines. Finally, the article proposes alternative terms for “artificial intelligence” to support more precise, critical, and ethically responsible language in educational contexts.
Keywords: artificial intelligence; large language models; chatbots; AI agents.

Resumen
Este artículo examina críticamente el uso del término “inteligencia artificial” en educación y sostiene que su empleo generalizado puede generar confusión conceptual y pedagógica. A partir de una revisión teórica apoyada en Pierre Lévy, Hubert Dreyfus, Sherry Turkle y Kate Crawford, se argumenta que los sistemas actualmente denominados “inteligentes” no piensan, no comprenden ni poseen intencionalidad, sino que operan mediante el reconocimiento estadístico de patrones a partir de datos generados por seres humanos. El texto analiza el origen histórico y filosófico del concepto de inteligencia, así como la evolución del término “inteligencia artificial”, para mostrar la distancia entre lo que estas tecnologías hacen y lo que su denominación sugiere. Asimismo, distingue entre IA discriminativa, IA generativa, grandes modelos lingüísticos, chatbots y agentes de IA, con el fin de evitar el uso indistinto de conceptos que implican funciones e implicaciones pedagógicas diferentes. También se cuestionan expresiones como “co-inteligencia” o “co-creación”, al atribuir una simetría problemática entre humanos y máquinas. Finalmente, se proponen términos alternativos a “inteligencia artificial” con el fin de promover un lenguaje más preciso, crítico y éticamente responsable en los contextos educativos.
Palabras clave: inteligencia artificial; grandes modelos lingüísticos; chatbots; agentes de IA.

1. Introduction

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"Artificial intelligence" appears everywhere today: in marketing, in media, and in the ubiquitous "AI-powered" label attached to everything from spam filters to photo editors. This inflation of meaning is not merely linguistic excess. It carries real consequences. In education, those consequences are amplified. Introducing the term into learning contexts without conceptual clarity risks miseducating the very learners we ask to use these tools responsibly. (Correia, 2026a).

2. The problem of naming: Rethinking "artificial intelligence" in education

If educators are to guide learners in the safe, ethical, and effective use of these systems, a clear understanding and honest discussion of what "artificial intelligence" is, and equally important, what it is not, becomes indispensable. Without this work, we risk building pedagogical practices on unstable conceptual ground.

In educational contexts, the stakes of imprecise language are particularly high. When we describe a tool as "intelligent," we implicitly suggest that it can teach, that it understands the learner, that it exercises judgment, and that it possesses some form of pedagogical authority. Each of these implications is highly debatable.

Along these lines, Cabellos et al. (2026) show that career-technical education students tend to perceive generative artificial intelligence more as an opportunity than as a threat to teaching and learning processes. However, the authors also caution that this positive perception should not obscure the risks associated with an uncritical or overly instrumental use of these tools, especially when they are used to produce assignments quickly without sufficient reflective engagement. This tension reinforces the need for greater conceptual and pedagogical precision when introducing these systems into educational contexts.

As Pierre Lévy (2023, 2025a, 2025b, 2025c, 2026) argues, intelligence emerges from a dynamic interplay between collective memory, individual cognition, and dialogical exchange. It follows, then, that the richer a learner's own knowledge base, the more meaningfully they can interact with computational tools. Human intelligence is therefore the prerequisite for productive use of these systems, not their product. To call the tool itself "intelligent" inverts this relationship and, in doing so, misrepresents where the real cognitive work takes place.

This leads to a central question: What does "artificial intelligence" actually mean, and is there more precise terminology that better reflects its nature? To answer this, we must begin with the origins of the term itself.

3. Where everything begins: The meaning of intelligence

The word intelligence derives from the Latin *intelligentia*, itself rooted in *intelligere*, meaning "to understand" or "to perceive." This term combines *inter* ("between") and *legere* ("to choose" or "to read"), suggesting that intelligence is fundamentally about discerning between things, making connections, and interpreting meaning.

Historically, this concept was never applied to tools or mechanisms. *Intelligentia* has often been attributed to conscious, reasoning beings, first divine and later human. It implied awareness, intentionality, and judgment. When we appropriate this term to describe machines, we are not making a neutral linguistic move. We are importing centuries of philosophical meaning into a contemporary domain where those assumptions may not apply.

Pierre Lévy (2023) provides a critical lens for examining this shift. He argues that the expression "artificial intelligence" is inherently misleading because it suggests autonomy and agency where none exists. The term carries connotations of consciousness and independent reasoning that machines do not possess.

Kate Crawford (2021) extends this critique by challenging both components of the term. She argues that these systems are neither truly "artificial," since they depend on material resources extracted from the earth and human labor, nor truly "intelligent," since they rely entirely on human-generated data. Her analysis reframes "artificial intelligence" as a socio-technical system grounded in human activity rather than machine autonomy.

Both Lévy and Crawford arrive at the same critical insight from different directions: what we call "artificial intelligence" is fundamentally rooted in human intelligence, and the term, as commonly used, obscures precisely that fact.

4. A brief history of the term "artificial intelligence"

The term "artificial intelligence" was first introduced by John McCarthy in 1955 in the proposal he co-authored with Marvin Minsky, Nathaniel Rochester, and Claude Shannon to organize what would become the Dartmouth Conference, a summer workshop held at Dartmouth College in Hanover, New Hampshire, in 1956. At the time, the term was aspirational. It captured the possibility that machines might one day perform tasks that, in a human, would be taken as evidence of intelligence.

Early research focused on symbolic reasoning, rule-based systems, and attempts to replicate human cognition. These efforts assumed that intelligence could be formalized and reproduced through logical operations. However, progress proved more difficult than anticipated, leading to periods of reduced funding and interest.

From the 1980s onward, the field shifted toward statistical methods and machine learning. Rather than attempting to replicate reasoning directly, researchers focused on pattern recognition and data-driven approaches. This shift intensified in the 2010s with advances in neural networks and large-scale data processing.

The recent surge of interest, particularly since 2022, is largely due to the public release of large language models and generative systems: computational tools trained on vast amounts of human-generated text and data, capable of generating fluent written responses, images, and other content that, to many users, appear remarkably human-like. These tools gave rise to widespread adoption and a renewed cultural fascination with "artificial intelligence." However, as Michael Jordan noted in discussions at the 2025 "AI, Science, and Society" conference in Palaiseau, France, these systems are fundamentally extensions of earlier predictive architectures rather than a realization of human-like intelligence.

This historical perspective reveals an important point: the meaning of "artificial intelligence" has shifted significantly over time. What began as a theoretical aspiration has become a broad and ambiguous label applied to a wide range of technologies.

5. What "artificial intelligence" actually means and does not mean

Lévy (2023, 2025a, 2025b) offers a compelling reframing. Rather than an autonomous intelligence, contemporary "artificial intelligence" can be understood as a statistical compression of collective digital memory. It mobilizes vast amounts of human-generated data and makes it accessible in new ways. As Lévy explains, "neural AI synthesizes and mobilizes the common memory accumulated over the centuries. Far from being autonomous, it extends and amplifies a stigmergic collective intelligence. Millions of users contribute to perfecting the models by asking them questions and commenting on the answers they receive" (p. 13, 2025a).

In this sense, it functions as an interface between collective intelligence and individual users. It does not think, understand, or intend. It retrieves, recombines, and predicts. This perspective aligns with Hubert Dreyfus's (1992) phenomenological critique of computational intelligence. Dreyfus argued that human intelligence is embodied. It emerges from lived experience, physical presence, and contextual awareness. Humans do not simply process information; they interpret it within a meaningful world shaped by experience.

Dreyfus distinguishes between "knowing-that" and "knowing-how." While machines can process explicit rules and patterns, they lack the intuitive, situational understanding that characterizes human expertise. This limitation remains evident in contemporary "artificial intelligence" systems.

Thus, both Lévy and Dreyfus converge on a shared conclusion: what we call "artificial intelligence" lacks the essential features of intelligence as traditionally understood, including consciousness, embodiment, intentionality, and meaning-making.

6. The problem with "co-intelligence" and similar framings

Recent terminology, such as "co-intelligence" and "co-creation," suggests a partnership between humans and machines. While appealing, this framing introduces conceptual problems.

The prefix "co-" implies symmetry. It suggests equivalence between human and machine contributions. However, this equivalence does not hold. Humans bring experience, emotion, ethical judgment, and intentionality. Machines operate through statistical pattern recognition.
Lévy (2025b) emphasizes that these systems function as intermediaries between collective and individual intelligence. They do not originate meaning; they redistribute it. The human remains both the source and the interpreter.

Sherry Turkle (2026) adds another dimension to this discussion through her critique of what she calls "artificial intimacy." She argues that conversational systems can simulate empathy without experiencing it, and that humans, in turn, may attribute understanding to these systems where none actually exists. This confusion, she warns, carries a social cost: as people increasingly turn to machines for connection, genuine human relationships risk being quietly eroded, giving way to isolation and loneliness. Her central question is particularly striking: "What do we forget when we talk to machines?" Her answer is equally direct: we risk forgetting what is idiosyncratic about being human.

Where Turkle draws attention to what is lost in human terms, Kate Crawford (2021) shifts the focus to what is concealed in material terms. Her analysis reveals that the very infrastructure of "artificial intelligence" depends on human input at every stage, from the creation of training data to the labor of model development and refinement. Far from autonomous, these systems are built upon and sustained by human work that largely remains invisible. To frame them as equal partners in any collaborative endeavor, whether creative, intellectual, or educational, is not only philosophically inaccurate but also politically misleading, as it obscures the profound dependency at the heart of every "artificial intelligence" system.

In summary, the prefix "co-" implies symmetry and mutual agency, that is, the equal contribution of two parties toward a shared goal. As the scholars examined in this essay make clear, human intelligence and machine processing are not equivalent and cannot be treated as such.

Humans bring embodied experience, emotional depth, moral agency, consciousness, and the capacity to generate meaning. These systems bring statistical pattern recognition, operating without consciousness, intention, or understanding. To describe this relationship as a partnership is not a harmless metaphor. It normalizes a fiction that obscures where genuine intelligence resides and gradually erodes our sense of responsibility for the knowledge we produce, the decisions we make, and the learners we educate.

7. Proposing alternative terms for "artificial intelligence"

If language shapes understanding, then reconsidering terminology becomes an ethical imperative. Instead of asking "How do we teach with 'artificial intelligence'?" we might ask, "How do we teach learners to engage critically with statistical pattern recognition systems?"

Several alternative terms may offer greater precision.

- **Collective memory interface.** Drawing directly from Lévy (2023), this term emphasizes that "artificial intelligence" systems provide access to accumulated human knowledge rather than generate intelligence of their own. In an educational context, a collective memory interface is a tool that makes the recorded knowledge of humanity accessible, but whose meaning is always activated by the living mind of the learner. The term makes no false claims to autonomy, consciousness, or intelligence.

- **Cognitive amplifier.** This framing highlights augmentation rather than replacement. It aligns with Lévy's (2025b) argument that these systems synergistically augment both individual and collective intelligence without replacing either. In educational contexts, it keeps the teacher and learner at the center and the tool in its proper supporting role, resisting what Turkle (2026) identifies as the drift toward tools that substitute for human relationships rather than enhance them.
- **Knowledge assistant.** This term places agency firmly with the learner. Drawing on Crawford (2021), who dismantles the myth of these systems as autonomous, and Dreyfus (1992), who reminds us that genuine intelligence is situated, embodied, and contextual, the term captures what a learner actually does with these tools: navigate a vast landscape of human knowledge. The system assists, but the navigation and the meaning-making remain entirely human activities.
- **Thinking support tool.** Inspired by Dreyfus (1992) and Turkle (2026), this term underlines the supplementary nature of these systems. Rather than framing the tool as a partner or collaborator, it positions it plainly as a support for human thinking, one that depends on the learner's own cognitive engagement to be meaningful. The term directly addresses Turkle's concern that learners may increasingly outsource not just tasks but thinking itself to machines. By naming the tool a support rather than an intelligence, it keeps the responsibility for thought where it belongs: with the human learner.

None of these alternatives is perfect, and no single term is likely to resolve a debate as complex as this one. But they move in a meaningful direction: toward conceptual clarity, critical reflection, and a more honest account of what these tools are and what they are not.

In educational contexts above all, the language we use to introduce and discuss these systems matters. It shapes how learners understand them, how educators frame them, and how institutions govern them. Replacing "artificial intelligence" with more precise terminology is not a merely academic exercise. It is an invitation to think carefully about the tools we have adopted, the assumptions embedded in the words we use to describe them, and the kind of education we wish to build around them.

8. Mapping the AI ecosystem: From discriminative AI systems to agents

To move toward more precise terminology, it is not enough to question the general use of the term “artificial intelligence.” It is also necessary to distinguish among the different systems and architectures that are often grouped under the same label. In current educational debates, terms such as AI, generative AI, large language models, chatbots, and AI agents are frequently used as if they were interchangeable, even though they refer to different technologies, functions, and pedagogical implications. Making these distinctions helps us ask better questions, calibrate expectations about what each system can do, and recognize more clearly where human judgment remains indispensable (Correia, 2026b).

8.1 Not all artificial intelligence is generative: Generative AI versus other forms of AI

To add further complexity to the terminological debate, the term "artificial intelligence" has become almost synonymous with tools such as ChatGPT. But this creates a misconception: not all AI systems generate content.

Historically, educational technologies have relied heavily on what scholars would call discriminative AI.

Discriminative AI refers to systems designed primarily to classify, predict, recommend, or select among existing possibilities. These systems analyze input and determine outcomes. In education, these earlier forms of AI were designed primarily to support decisions rather than generate content or "answer" inquiries. Intelligent tutoring systems, adaptive learning platforms, automated grading tools, student success prediction models, and content recommendation systems all used data to identify patterns and suggest next steps.

Generative AI operates differently because it does not simply classify information, recommend a next step, or select from a fixed set of options. Instead, it creates new outputs by drawing on patterns learned from large datasets. Tools such as ChatGPT, Claude, and Gemini can generate text, images, code, audio, examples, explanations, and other forms of content in response to a prompt (inquiry). In education, this changes the nature of the interaction: users are no longer asking only, "Which student needs support?" or "Which lesson comes next?" They are asking, "Can you rewrite this?" "Can you summarize this?" "Can you help me brainstorm ideas?" or "Can you create an example I can use in class?" The system becomes less like a decision-support tool and more like a generative partner that can help draft, revise, explain, simulate, and create materials. This shift expands what AI can do in educational settings, while also making human judgment even more important in evaluating accuracy, relevance, tone, and pedagogical value.

The distinction between discriminative AI and generative AI matters because educational expectations vary depending on which category of system we are using. Discriminative AI supports decisions by identifying patterns and recommending possible actions. Generative AI supports creation by producing new content, explanations, and examples. Confusing the two can lead us to ask the wrong questions, overstate what a system can do, or overlook where human judgment is most needed.

8.2 Large language models explained

Once generative AI enters the conversation, another term appears immediately: *large language models* (LLMs). Are LLMs and generative AI the same thing? Not exactly. Generative AI is the broader category, and large language models are one specific type of generative AI. LLMs are designed to work with language. An LLM is a computational model trained on extremely large collections of text to predict likely sequences of words. This may sound technical, but the basic idea is fairly straightforward. If discriminative AI functions like an evaluator deciding among existing options, an LLM works more like an advanced completion engine, predicting what text should come next. For educators, this distinction is important because it shapes what we should expect from these systems and how carefully we must interpret and critically analyze their responses. The human interaction with LLMs is also different. When educators use an intelligent tutoring system or another form of discriminative AI, the question is often, "What should happen next?" The system evaluates available data and recommends a pathway, intervention, score, or resource. When educators use an LLM, however, the question shifts toward, "What could happen?" The system can draft an explanation, suggest an example, simulate a dialogue, reframe a concept, or generate possibilities that did not previously exist in that exact form.

This is one reason "prompting" has become so important. Prompting is not merely a technical procedure. It is a way of communicating context, goals, constraints, and human intention into a generative system. For educators, this means that the quality of the interaction depends not only on the sophistication of the model but also on the clarity, purposefulness, and pedagogical judgment embedded in the prompt (Correia et al., 2025).

8.3 From chatbots to AI agents: A new layer of confusion

If generative AI introduced new confusion into educational terminology, agentic AI has intensified it. Terms such as *chatbot* and *AI agent* are now often used interchangeably, even though they do not necessarily describe the same thing.

A *chatbot* is best understood as an interface. It is defined largely by how humans interact with it, usually through text or voice. Earlier chatbots followed relatively simple rules: a user entered a question or command, and the system produced a programmed response. Modern chatbots often incorporate large language models, which allow them to generate more flexible and conversational replies. Still, the defining feature is the interaction itself. A chatbot is defined primarily by how humans interact with it.

An *AI agent*, by contrast, is defined less by how it communicates and more by what it can do. An agent can receive goals, make decisions, use tools, complete multiple steps, maintain memory, and adapt its outputs along the way.

In education, this distinction matters. A chatbot may answer the question, "How should I create a lesson?" An AI agent may move beyond the conversation by creating lesson materials, generating assessments, revising content, organizing files, and preparing student summaries. The interaction shifts from information retrieval to delegated work to an AI assistant.

This evolution does not eliminate the need for conceptual precision; on the contrary, it makes it more urgent. The more capable these systems appear to be of acting, the more important it becomes to clearly describe what they do, what they do not do, and what kind of human responsibility remains necessary in their use in educational contexts.

9. Conclusion: Toward a more honest terminology

Language is never neutral. The words we use to describe technology shape how we understand it, how we regulate it, and how we integrate it into education. The term "artificial intelligence," rooted in the deeply human concept of *intelligere*, carries assumptions that distort our understanding of these systems. Despite their practical success, there remains a gap between what these systems do and what the term suggests. The authors examined in this article converge on a shared insight regarding the human foundations embedded in the term "artificial intelligence." In this regard, Lévy reframes these systems as interfaces of collective intelligence; Dreyfus reminds us that true intelligence is embodied; Turkle warns against confusing simulation with experience; and Crawford reveals the material and human foundations of these technologies. Taken together, their work calls for greater precision and intellectual honesty. This precision is not limited to questioning the term "artificial intelligence" in a general sense. It also requires distinguishing among different forms of AI, such as discriminative systems, generative AI, large language models, chatbots, and AI agents. Each of these categories entails different functions, capabilities, and pedagogical risks. Confusing them can lead to mistaken expectations, poorly grounded institutional decisions, and educational practices that fail to adequately recognize where human judgment is required.

The need to recognize where human judgment is required is especially critical in education. When we fail to distinguish among different forms of AI and describe these systems as "intelligent," we risk attributing to them an authority they do not possess. We also risk encouraging learners to outsource thinking rather than develop it. Likewise, when we use terms such as generative AI, LLM, chatbot, or agent as if they were equivalent, we obscure the differences that should guide their pedagogical, ethical, and institutional use.

The goal is not to diminish the value of tools that are generically described as "intelligent." Indeed, these tools are effective and valuable. The goal is to describe them with precision and rigor, in a way that preserves human agency, responsibility, and understanding. The terminology we choose should not attribute to these tools a status they do not possess. Rather, it should clarify their function, recognize their limitations, and reaffirm what no computational system can replace: the living, thinking, and feeling human being at the center of every meaningful act of learning.

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