# New Literacies in the Age of AI: Ethics, Teaching, and Writing (English Version)


AG EDITOR

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Rubén González Vallejo (Ed.)

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# Preface

Writing and teaching have never been neutral acts.

What we put into words, how we share them, with whom we debate them, and from where we produce them shapes not only knowledge, but also the very possibilities of imagining futures. In this era, marked by generative artificial intelligence, that statement takes on a new intensity. It is no longer just about learning to use tools; it is about asking ourselves what kind of literacy we need in order not to lose sight of the true meaning of education.

This book was born precisely from that concern — from an urgent and shared need among those of us who inhabit the world of education to rethink our practices, our certainties, and our roles in the face of technologies that write, correct, give feedback, and — at times — even decide for us. It is not about fearing AI, nor about celebrating it naively, but about building a critical, ethical, and situated literacy that allows us to teach *with* it, not *in spite of* it.

Here, diverse voices come together: teachers, researchers, educators, and creators who have chosen to look this new landscape squarely in the eye. The chapters in this volume are as varied as they are necessary: there is theory, yes, but also practice. There are warnings, proposals, experiences, and pathways that are only beginning to take shape.

This book does not have all the answers. But it does have the right questions — and with them, an open invitation to collectively rethink what it means today to write and teach with artificial intelligence.

Welcome to this dialogue.

Rubén González Vallejo (Ed.)

# Introduction

This book emerges from a shared urgency: the need to understand, confront, and reinterpret the changes that generative artificial intelligence is producing in the field of education. Although the emergence of these technologies has been rapid, their effects are neither neutral nor automatic. Every tool, every use, every pedagogical decision entails an ethical, political, and epistemological stance. In this context, speaking of literacy cannot be limited to technical skills or platform mastery. It is necessary to speak of a new literacy—one that enables us to read the present critically and to write the future actively, even when writing is no longer solely a human act.

The work the reader holds in their hands brings together eleven chapters that reflect upon, experiment with, and problematize teaching, assessment, and academic production in times of artificial intelligence. The voices assembled here come from different regions, disciplines, and educational levels, yet they all share a common concern: how to keep the formative essence of education alive amid automatisms that threaten to reduce it to mere mechanics. There is no single answer here, nor a replicable formula. What we find instead is a collective endeavor to think about education from the standpoint of complexity—with rigor and imagination.

The first chapters outline a conceptual framework that redefines literacy through digital, ethical, and pedagogical lenses. They stress the urgency of preparing teachers who are not only capable of integrating technologies but of doing so critically, from a situated and conscious perspective. The figure of the educator is reclaimed as a cultural and epistemological mediator—someone able to interpret algorithmic discourses and re-signify them within diverse contexts. In this section, the role of AI in reading, writing, and planning processes is questioned, highlighting the need for methodologies that promote autonomous thinking and critical awareness.

The middle chapters present teaching experiences in which AI is incorporated as a tool to enrich learning without displacing the teacher or automating the pedagogical relationship. Through the design of resources, the implementation of instructional strategies, and the use of AI for feedback, possible scenarios are shown in which technology enhances teaching without dehumanizing it. These experiences demonstrate that the integration of AI is not an inevitable destiny but a pedagogical decision that requires intentionality, design, and guidance.

In the final part of the book, the focus shifts to the ethical, legal, and evaluative challenges that arise with artificial intelligence. Questions about authorship, plagiarism, traceability of academic production, and the validity of assessment become central. In response to these tensions, the authors propose approaches that go beyond surveillance or prohibition, advocating instead for an ethics of process, more comprehensive evaluation practices, and a redefinition of merit and originality in contexts mediated by generative technologies.

Throughout its pages, this book offers neither a homogeneous perspective nor definitive conclusions. Its strength lies precisely in the diversity of viewpoints, in the ability to sustain complex questions, and in the collective effort to construct shared meaning. Artificial intelligence is here to stay—but what we do with it—in classrooms, curricula, texts, and our everyday practices—has yet to be written. This work is an invitation to take part in that writing, with responsibility, critical thought, and a steadfast commitment to the pedagogical as a profoundly human act.

# Abstract

This collective volume addresses the challenges and possibilities of digital and ethical literacy in the contemporary educational context, which is profoundly shaped by the emergence of generative artificial intelligence. Across eleven chapters, educators and researchers from various countries analyze how AI is transforming writing, teaching, assessment, and teacher education from pedagogical, legal, technological, and epistemological perspectives.

The content is organized into three modules. The first focuses on the conceptual foundations of new literacies and their impact on teacher training. The second brings together pedagogical experiences that integrate AI into instructional design, feedback, and academic creativity. The third module examines the ethical and legal implications of AI use in contexts of authorship, academic integrity, and evaluation.

Far from offering a unified or prescriptive vision, the chapters invite readers to critically reflect on the role of AI in teaching and learning processes, as well as to explore practical proposals and frameworks for responsible and formative integration. This work is aimed at teachers, trainers, researchers, and educational policymakers interested in understanding, applying, and teaching with AI from a critical, ethical, and contextualized perspective.



**Keywords:** Digital Literacy; Academic Authorship; Educational Assessment; AI Ethics; Teacher Education; Artificial Intelligence.

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# Chapter 01 / Capítulo 01

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# The New Literacy in the Age of AI: Educational Foundations, Pedagogical Practices, and Ethical Challenges

## La nueva alfabetización en tiempos de inteligencia artificial: fundamentos, prácticas y desafíos

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**ABSTRACT**

This chapter examines the transformation of literacy and writing in the era of artificial intelligence (AI), addressing cultural, pedagogical, ethical, and cognitive implications. It develops four sections: theoretical foundations of new literacy, innovative teaching practices across educational levels, tools and ethical/evaluative challenges, and future perspectives on teacher education.

Significant changes in writing are highlighted, where AI functions as a co-author, redefining authorship and educational practices. In primary, secondary, and higher education, classroom projects, guided writing, critical essays, and AI-assisted academic production are discussed, along with teacher communities fostering collaborative innovation. The tools and ethics section explores prompt design, responsible use, authorship, and institutional guidelines.

Findings indicate that literacy in the AI era does not replace human thinking but expands, enhances, and diversifies it, fostering critical, ethical, and creative competencies. AI should be integrated as a co-author and mediator in education, promoting reflection, creativity, and analytical thinking while maintaining intellectual autonomy.

**Keywords:** Artificial Intelligence; Literacy; Education; Ethics; Generative Writing; Teacher Training; Prompt Design.

**RESUMEN**

El presente capítulo analiza la transformación de la alfabetización y la escritura en la era de la inteligencia artificial (IA), considerando implicaciones culturales, pedagógicas, éticas y cognitivas. Se desarrollan cuatro secciones: fundamentos teóricos de la nueva alfabetización, prácticas docentes innovadoras, herramientas y desafíos éticos y de evaluación, y perspectivas futuras sobre la formación docente.

Se evidencian cambios significativos en la conceptualización de la escritura, donde la IA actúa como coautora de textos, transformando la autoría y las prácticas educativas. En educación básica, media y superior, se presentan experiencias con proyectos del aula, escritura guiada, ensayos críticos y producción académica asistida por IA, así como comunidades docentes para innovación colaborativa. La sección de herramientas y ética aborda el diseño de *prompts*, límites de uso, autoría responsable y lineamientos institucionales.

Los hallazgos sugieren que alfabetizar en tiempos de IA no reemplaza el pensamiento humano, sino que lo amplía, potencia y diversifica, promoviendo competencias críticas, éticas y creativas. Se plantea la necesidad de integrar la IA en la educación como coautora y mediadora del aprendizaje, fomentando la reflexión crítica y la creatividad, sin perder la autonomía intelectual.

**Palabras clave:** Inteligencia Artificial; Alfabetización; Educación; Ética; Escritura Generativa; Formación Docente; Diseño De *Prompts*.

## INTRODUCTION

We are living in a time of profound cultural transformation in which artificial intelligence has burst onto the scene as an unprecedented tool for symbolic production. Writing, historically understood as an exclusively human practice, is now shared with systems capable of generating coherent, creative, and argumentative text. This reality is reshaping not only the act of writing, but also teaching, reading, and academic assessment.

Literacy has evolved significantly with the emergence of artificial intelligence (AI) and generative tools, transforming the act of writing and learning (Bazerman, 2013; Gee, 2015; Floridi, 2023). This transformation involves cultural and pedagogical changes that require a critical and ethical approach (Floridi, 2019; Selwyn, 2023). Education faces the challenge of integrating these technologies into the classroom to foster creativity, critical thinking, and skill development (Luckin et al., 2016; Holmes et al., 2021).

In the educational context, AI presents challenges and opportunities. While some sectors warn of the risk of technological dependence or loss of authenticity, others recognize its potential to expand creativity, personalize learning, and democratize access to knowledge (Selwyn, 2019; Luckin et al., 2016). In this scenario, the notion of *new literacy* emerges, understood as the ability to read, write, analyze, and produce critically with digital and intelligent tools.

The purpose of this chapter is to explore the theoretical foundations, emerging teaching practices, and ethical challenges associated with AI writing. Throughout the sections, we analyze the cultural and pedagogical implications of AI as a co-author, experiences of generative literacy at different educational levels, and the policies necessary for ethical and inclusive use of the technology.

## DEVELOPMENT

### SECTION 1. THE NEW LITERACY: FOUNDATIONS AND CHALLENGES

#### 1.1. Writing in the age of artificial intelligence

Writing has always been a cultural act deeply linked to thought, memory, and identity. Throughout history, technological changes—from the invention of the alphabet to the printing press and the computer—have redefined the ways we write, read, and transmit knowledge. However, the emergence of artificial intelligence represents a different qualitative leap: for the first time, technology not only facilitates writing, but *writes with us*.

Writing in the age of AI redefines the act of writing, with AI acting as a co-author and collaborator in the creation of texts (Bender et al., 2021; Boden, 2016). Literacy in the age of AI involves developing critical thinking, digital skills, and ethical awareness (Floridi, 2023; Ng, 2021). Teaching practices are transformed through the incorporation of generative tools and the modification of teaching skills and strategies (Mishra & Koehler, 2006; Luckin et al., 2022).

In this new scenario, AI becomes an *algorithmic co-author* (Boden, 2016), capable of generating texts with semantic coherence, logical argumentation, and a style adaptable to the context. Tools such as ChatGPT, Claude, Copilot, and Gemini do not merely process information: they interpret complex linguistic instructions, learn discursive patterns, and respond with outputs that mimic the human voice. This phenomenon marks a paradigm shift in the conception of writing as an exclusively human process.

From a cultural perspective, this change leads to a *decentralization of authorship*. The text no longer belongs solely to the person who signs it, but emerges from the interaction between the human mind and artificial intelligence. This raises questions about authenticity, creativity, and originality. Can the user who guides textual production through *prompts* be considered a "writer"? Where does human creativity begin, and where does algorithmic intelligence end?

Boden (2016) suggests that creativity does not disappear in this process, but instead transforms. The human writer ceases to be the sole producer of ideas and becomes a *cognitive curator*, an architect of meanings who designs, selects, and evaluates the responses generated by AI. In this sense, AI acts as an extension of the human mind, an *epistemic instrument* that amplifies expressive capacity, but also demands new skills in control, analysis, and ethics.

Floridi (2019) argues that we live in an "information society" where data and algorithms mediate reality. Writing, therefore, involves constantly negotiating with intelligent systems that filter, recombine, and propose meaning. In this context, traditional literacy—focused on decoding letters and constructing sentences—is insufficient. Writing in the age of AI demands *algorithmic literacy*, understood as the ability to understand, monitor, and question the invisible structures that generate text.

An illustrative example can be found in academia: a university student uses ChatGPT to write an essay on environmental ethics. The AI produces a formally correct text, but with generic arguments and no cultural nuances. The student's task is no longer to check spelling, but to identify conceptual gaps, add references, and give the text a *human voice*. In this way, AI-assisted writing becomes a dialogical exercise: the human reinterprets, corrects, and enriches what the machine proposes.

The transformation of the act of writing also raises pedagogical tensions. On the one hand, the use of AI can encourage superficiality—copying and pasting generated texts—but, on the other hand, it can encourage metacognitive reflection by comparing different versions of a text or analyzing how the response changes depending on the *prompt* used. Thus, AI-assisted writing should not be seen as a threat, but as an opportunity to strengthen understanding of the writing process, highlighting the importance of intention, structure, and communicative purpose.

### 1.2. What does literacy mean in the age of artificial intelligence?

In the digital age, literacy is no longer limited to teaching reading and writing, but rather to educating critical citizens capable of interacting with complex information in algorithm-mediated environments. According to Ng (2021), *new literacy* combines technical skills (knowing how to use digital tools), cognitive skills (thinking critically about information), and ethical skills (deciding responsibly how and when to use technology).

In the age of AI, literacy means teaching people to understand how automatic text generation works, how to identify biases in results, and how to distinguish between validated knowledge and plausible but false content. This type of literacy also requires developing *algorithmic awareness*: understanding that every AI response reflects the system's limitations, values, and training data.

From a pedagogical perspective, this literacy requires an interdisciplinary approach. Teachers no longer teach only grammatical rules or argumentative structures, but become mediators between language, technology, and ethics. Education must foster experiences in which students engage in dialogue with AI, question its results, and build knowledge through the contrast between what is generated and what is researched.

For example, a classroom exercise could consist of asking AI for a text on “the social impact of climate change” and asking students to identify which parts of the text lack evidence or reproduce stereotypes. This process stimulates critical thinking and promotes *augmented reading*: active reading that does not accept information as truth, but subjects it to verification and analysis.

Furthermore, literacy in the age of AI involves incorporating digital ethics as a cross-cutting theme in the curriculum. Students must reflect on authorship, data privacy, consent, and intellectual property. These discussions are not merely technical, but deeply moral: Is it ethical to use AI to produce academic work without declaring it? How can intellectual integrity be protected when machines can generate texts?

Selwyn (2019) emphasizes that educating in AI does not mean teaching how to use software, but how to *think with software*. Contemporary literacy, then, is oriented toward developing citizens capable of understanding the political and cultural role of technology, not just its operational functionalities.

### 1.3. Writing, teaching, and learning with generative tools

The educational process is undergoing an unprecedented metamorphosis. AI is transforming not only individual writing, but also the dynamics of teaching and learning. In classrooms, generative tools enable the exploration of new forms of *creative learning*, where students become content designers, and teachers become facilitators of cognitive experiences.

Luckin et al.(2016) propose the concept of *augmented educational AI*, which does not replace teaching but rather enhances it. Algorithms can analyze student progress, suggest personalized activities, and offer immediate feedback. However, the human dimension remains irreplaceable: only teachers can interpret the emotions, motivations, and contexts that AI cannot understand.

In this sense, writing with AI becomes a practice of *pedagogical co-authorship*. Students learn to negotiate with the tool, adjusting parameters, reformulating *prompts*, and evaluating results. Each interaction is an act of metacognitive thinking: by observing how AI responds, learners discover their own cognitive and discursive patterns.

For example, a university workshop can incorporate a teaching sequence in which students write an introduction with the help of AI, review it as a group, and finally produce an individual final version. This process highlights the importance of critical reflection and human collaboration in the use of generative tools.

From a teaching perspective, teaching with AI involves reconfiguring assessment strategies. The traditional approach—focused on the final product—must give way to a *process-based assessment* that evaluates decision-making, justification of AI use, and the ability to reinterpret results. This change requires specific teacher training in digital ethics, educational *prompt* design, and discourse analysis.

Finally, learning with AI also means learning to set limits. Not everything should be automated: writing remains a space for subjective expression, imagination, and experience. AI can be a guide, a mirror, or an assistant, but never a substitute for the human voice. Comprehensive literacy must ensure that students do not lose their ability to think, feel, and create autonomously.

**Summary of Section 1**

Writing in the age of artificial intelligence does not represent the end of traditional literacy, but rather its expansion into new cognitive and ethical dimensions. Literacy today means educating individuals who can understand the language of machines without losing the essence of human thought.

The educational challenge lies in balancing technological efficiency with critical depth, promoting a collaborative relationship between human and artificial intelligence. Only through comprehensive literacy—combining technique, ethics, and creativity—will it be possible to inhabit the new digital ecosystem of knowledge responsibly.

## SECTION 2. TEACHING PRACTICES AND REAL-LIFE EXPERIENCES

### 2.1. Generative literacy in basic education

Literacy in basic education is the foundation upon which the communicative, cognitive, and social skills of future citizens are built. At this level, the challenge is to integrate artificial intelligence (AI) as a learning tool without replacing the development of symbolic thinking, imagination, and personal expression.

In basic education, generative literacy enables AI-supported classroom projects and guided writing, promoting creativity (Fullan, 2021; Lévy, 2019). In secondary education, AI is used to write essays and develop argumentation and critical review skills (Sahlberg, 2023; Selwyn, 2019). Academic and professional writing benefits from AI in papers, reports, and teacher reflections (OECD, 2023). H y communities of practice strengthen collaboration and pedagogical innovation (Wenger, 1998; Williamson & Piattoeva, 2022).

*Generative literacy* is defined as the ability to create, understand, and modify content produced jointly with AI systems (Ng, 2021). In basic education, this involves introducing children to the responsible, guided use of tools that generate text, images, or stories from verbal or written instructions. It is not about teaching programming or encouraging technological dependence, but instead accompanying students in exploring new forms of representation and communication.

An example of a classroom project focused on this literacy can be developed around guided collaborative story writing. The teacher proposes an initial situation—for example, “a girl travels into space to save a planet in danger”—and the students, with the help of generative AI, create descriptions, dialogues, or endings. The emphasis is not on the final textual product, but on the process: reflecting on which AI suggestions are helpful, which should be rejected, and why.

This type of experience promotes critical and metacognitive thinking from an early age. Children learn that AI is not an infallible source, but rather a tool that requires human guidance and judgment. As Gee (2015) points out, modern literacy must be *situated*; that is, it must contextualize learning within meaningful social practices. By writing with AI, students not only learn to use technology but also participate in a contemporary discursive community where creativity is collaboratively built.

From the teacher’s perspective, implementing these practices requires a curriculum redesign that incorporates digital skills, critical thinking, and ethics. AI can support pedagogical differentiation by offering suggestions tailored to each student’s reading and writing levels, enabling more inclusive teaching. However, it also poses risks: overexposure to generated texts can limit original expression or reinforce cultural biases present in language models (Bender et al., 2021).

Therefore, generative literacy in basic education must be based on three essential pedagogical principles:

1. Constant human mediation: AI does not replace the teacher, but acts as a cognitive assistant under their supervision.
2. Ethical and cultural reflection: Students should discuss the implications of creating with machines, recognizing the value of authorship and authenticity.
3. Experiential learning: AI should be integrated into meaningful, grounded projects aligned with students' interests.

These principles ensure that AI becomes a means of expanding the imagination rather than reducing intellectual autonomy.

### 2.2. AI in secondary education: writing to think

In secondary education, students face more complex writing tasks: argumentative essays, scientific reports, and critical analyses. In this context, AI becomes a powerful tool for thinking through writing. Writing to think, as Bazerman (2013) states, involves using the act of writing not only to communicate ideas but to construct, refine, and understand them in depth.

Generative AI tools, such as ChatGPT or Gemini, can facilitate this process by generating drafts, outlines, or counterarguments. However, the educational value lies in their thoughtful use. For example, a teacher may ask students to use AI to produce an introduction to an essay on social inequality. Students must then critically analyze the generated text: What assumptions does it contain? What does it omit? What kind of language does it use? Is it neutral, or does it reproduce biases?

This type of activity encourages *critical thinking* and *discursive awareness*. Students learn to identify the ideology underlying algorithmic language, understanding that all textual generation reflects particular values, data, and perspectives (Floridi, 2019). In addition, this practice helps improve argumentative competence, as students must justify their acceptance or rejection of an AI response.

AI can also act as *cognitive scaffolding* (Vygotsky, 1978), providing examples or writing models that students adapt to their own style. However, teachers must establish clear criteria for authorship and originality. Secondary education should teach not only how to use AI, but also how to engage in dialogue with it, while maintaining the centrality of human judgment.

A particularly valuable practice involves critically reviewing AI-generated text. This dynamic encourages students to compare an automatic version with one they have written themselves. The subsequent discussion, guided by the teacher, allows them to identify the strengths and weaknesses of both pieces of work. This promotes *formative assessment*, focusing on the process of improvement rather than the final grade.

In short, AI in secondary education can become a laboratory of thought where the most necessary skills for the 21st century are trained: discernment, argumentation, ethics, and creativity. Far from weakening learning, its well-planned incorporation can strengthen it by offering new avenues for intellectual exploration.

### 2.3. Academic and professional writing with AI

In higher and professional education, writing serves specific cognitive, communicative, and social functions: building knowledge, disseminating research results, and participating in academic communities. At this level, AI represents both an opportunity for efficiency and an ethical and epistemological challenge.

The use of AI for writing *papers*, reports, or teaching reflections has spread rapidly. Tools such as Scite, Elicit, and ChatGPT allow users to synthesize bibliographies, suggest argumentative structures, and generate summaries. However, as Nature (2023) warns, irresponsible use can lead to the "automation of scientific appearance," that is, to texts that are formally correct but lack rigor.

Therefore, AI should be conceived as a *cognitive assistant* rather than an author. Its ideal role is to enhance intellectual productivity, helping researchers formulate questions, organize ideas, and review writing, without replacing critical judgment or theoretical analysis.

A concrete example can be seen in the process of writing an academic article:

1. The author uses AI to generate a list of possible titles and section outlines.
2. They review the suggestions, adapt them to their approach, and complete the argument.
3. Finally, they use AI to check for textual consistency and grammatical correctness.

This workflow reflects responsible collaboration, where AI optimizes efficiency without compromising scientific integrity.

In addition, AI can play a key role in university teacher training. Teachers can use it to design rubrics, personalized feedback, or examples of academic writing. This promotes teaching based on modeling and reflection.

However, it is also necessary to recognize the risks. Generative systems can reproduce biases or plagiarize unidentifiable fragments. In this sense, the *critical literacy in AI* proposed by Selwyn (2019) and Williamson & Piattoeva (2022) becomes essential: professionals must be aware of the tool's limitations, the conditions of its training, and the implications of its use in assessment or publication contexts.

AI-assisted professional writing, therefore, redefines the role of the author: from producer to editor, from executor to strategist. The quality of writing will not depend on typing skills, but on the *cognitive competence to guide and validate automatic generation*. In this new paradigm, knowing how to write becomes *knowing how to direct artificial intelligence to write meaningfully*.

### 2.4. Teacher training and communities of practice around AI

The effective incorporation of AI into education requires prepared, critical, and creative teachers. *Teacher training in generative literacy* cannot be limited to technical courses on software use, but must focus on developing an epistemological and ethical understanding of the technology.

According to Mishra and Koehler (2006), teacher competence in technology is based on the integration of technological, pedagogical, and disciplinary knowledge (TPACK model). In the context of AI, this integration involves knowing when, how, and why to use generative tools to promote meaningful learning.

Communities of practice (Wenger, 1998) are ideal spaces for this training. In them, teachers share experiences, reflect on the results obtained, and build collective pedagogical knowledge. For example, a network of language teachers can exchange strategies for using AI to teach argumentation without encouraging plagiarism.

These communities not only promote pedagogical innovation but also act as ethical support networks. In the face of technological enthusiasm, it is necessary to maintain a critical dialogue about limits and responsibilities. Decisions about the use of AI must be discussed collectively, recognizing the diversity of contexts, resources, and educational values.

A relevant example is the collaborative work between Latin American universities that implement digital literacy and AI laboratories. In these spaces, teachers experiment with generative tools, design interdisciplinary projects, and reflect on the social and cultural impacts of algorithmic approaches to teaching. These experiences show that the most valuable pedagogical innovation arises from peer exchange rather than from adopting external technologies.

Finally, teacher training in AI must promote a new type of *educational leadership*: one that combines emotional intelligence, critical thinking, and digital competence. Teaching with AI means teaching with intelligence, not fear. It means recognizing the transformative potential of technology without renouncing the humanistic principles that underpin education.

As Fullan (2021) concludes, sustainable educational change occurs when teachers feel they are protagonists in the process and not simply users of tools. Therefore, AI literacy should be conceived as a collective, continuous, and reflective process that strengthens professional autonomy and ethical innovation in the classroom.

**Summary of Section 2**

Teaching practices and real-world experiences show that artificial intelligence can become a powerful ally for contemporary literacy when integrated from a critical, ethical, and pedagogically grounded perspective.

In basic education, AI fosters guided creativity; in secondary education, it enhances argumentation and critical thinking; in higher education, it increases productivity and academic rigor; and in teacher training, it promotes communities of learning and ethical innovation.

The central challenge is to balance automation and humanization, efficiency and reflection. The education of the future will not be based on teaching people to compete with AI, but on teaching them to collaborate with it consciously, maintaining the centrality of human judgment, emotion, and ethics in all teaching and learning processes.

## SECTION 3. TOOLS, ETHICS, AND ASSESSMENT

### 3.1. Designing educational *prompts*: the new digital competency

The design of *prompts*—linguistic instructions that guide generative AI models—has become a core competency of contemporary literacy. In the educational context, this skill transcends the technical and transforms into a new pedagogical language: educational prompting. Knowing how to communicate with artificial intelligence involves understanding the structure of language, the logic of algorithms, and the pedagogical intentions behind each question or request (Ng, 2021).

The design of educational prompts becomes a key competency, facilitating pedagogical interaction with AI (Holmes et al., 2021; Ng, 2021). Detecting and delimiting the use of AI requires establishing ethical boundaries and ensuring responsible authorship (UNESCO, 2021; UNESCO, 2023). Institutional policies promote critical literacy and regulate the incorporation of AI in education (Luckin et al., 2016; Selwyn, 2023).

The *prompt* is not a simple command, but rather a cognitive mediation. It allows human intention to be translated into an instruction that is understandable to the machine. In this sense, teachers who master the design of *prompts* become architects of algorithmic thinking: they guide AI toward an educational purpose, preventing responses from being superficial or disconnected from educational objectives.

From an educational perspective, educational *prompting* serves three main functions:

1. Exploratory function: it allows students to investigate ideas, generate hypotheses, or discover new perspectives. For example, a *prompt* such as “compare the social causes of poverty in Latin America and sub-Saharan Africa” invites AI to structure information for students to analyze critically.
2. Reflective function encourages metacognition, as the learner observes how their formulation of the question affects the quality of their response.
3. Creative function: it drives the production of original texts, scripts, stories, or projects based on established parameters.

However, mastering this skill does not mean relying on AI to generate knowledge; instead, it means learning to engage in critical dialogue with it. As Selwyn (2019) warns, education must prioritize critical thinking over uncritical automation. Teaching *prompting* involves teaching how to ask good questions, contextualize, and evaluate responses based on ethical and epistemological criteria.

From a teaching perspective, *prompting* can be conceived as a new pedagogical metalanguage. Designing effective instruction requires conceptual clarity, communicative intent, and disciplinary knowledge. A poorly formulated *prompt* can lead to erroneous or biased responses, while a well-structured one encourages in-depth exploration of the content. For this reason, some authors (Holmes et al., 2021) propose including *prompt design* in the digital teaching skills curriculum.

In practice, teachers can use different educational *prompting* strategies:

- Prompt by cognitive levels: linked to Bloom’s taxonomy. Example: “Explain,” “Compare,” “Analyze,” “Evaluate.”
- Role-based prompt: assigning roles to AI (“act as a historian,” “as an academic writer,” etc.) to obtain contextualized perspectives.
- Metacognitive prompt: inviting the AI to reflect on its own response (“What are the limitations of your argument?”).
- Ethical prompt: introducing moral dilemmas (“What consequences would this decision have for different social groups?”).

These approaches promote a reflective, formative use of AI rather than mere instrumental dependence.

Therefore, *educational prompting* is configured as a new discursive literacy. It is not enough to "use AI": it is necessary to teach how to think with it, understand its biases, validate its contributions, and question its limits. In Floridi's (2019) words, human intelligence must remain the "moral and epistemological filter" of all digital interaction.

**3.2. Detecting, analyzing, and delimiting the use of AI: ethical limits, evaluation, and responsible authorship**

As generative AI tools are integrated into the educational environment, a central concern arises: how to ensure ethical and responsible use. This question encompasses three key dimensions: detecting misuse, evaluating AI-mediated productions, and defining authorship in academic contexts.

The first dimension, detection, has become more relevant as automated systems have developed to identify AI-generated text. However, recent research (Mitchell et al., 2023) shows that these detectors have significant error margins, leading to false positives and harming innocent students. Therefore, experts agree that the solution is not technical but pedagogical: instead of "hunting" for AI use, it should be integrated into assessment practices, promoting transparency and ethical reflection.

One possible strategy is to incorporate an AI collaboration statement into assignments. Students explicitly state which tools they used, at what stage of the process, and for what purpose. This approach, already adopted by universities such as Harvard and the UOC, encourages academic honesty and transparency and allows evaluation not only of the final product but also of the decision-making process.

The second dimension, assessment, requires a thorough review of traditional criteria. If AI is involved in generating ideas or drafts, what is being assessed: technical skill, critical thinking, or supervisory ability? The answer lies in refocusing assessment on thinking skills rather than just the text produced.

Teachers can design activities that value the ability to analyze AI responses, identify errors, or improve consistency. In this way, students demonstrate understanding and judgment, rather than simple reproduction. According to Luckin et al. (2016), this form of assessment promotes *augmented intelligence*, understood as the synergy between human creativity and technological support.

The third dimension, responsible authorship, is one of the most complex debates of the 21st century. UNESCO (2023) has noted that AI-generated texts lack copyright protection, as algorithmic creativity lacks intention or consciousness. However, when a human author guides, edits, and validates the result, a hybrid form of co-authorship is produced.

In academia, this raises ethical dilemmas: Is it legitimate to include AI-generated fragments in a research paper without citing the source? International publication guidelines (such as those from Elsevier and Springer) state that AI can be used for technical support but should never be listed as an author. In addition, any algorithmic intervention must be explicitly declared.

In the educational context, it is recommended that students be taught to apply three basic principles of ethical authorship:

1. Transparency: always indicate whether AI has been used and for what purpose.
2. Responsibility: take responsibility for reviewing and validating all generated

content.

3. Criticism: Do not passively accept results, but analyze them from a reflective standpoint.

These principles ensure that learning remains human, even when mediated by technology. The goal is not to ban AI, but to educate citizens who can coexist ethically with it.

In short, the ethics of AI use are not based on prohibition, but on the user's critical awareness. Detecting and delimiting its use requires institutional policies, teacher support, and a culture of transparency that reinforces trust and intellectual responsibility.

### 3.3. Policies and recommendations for critical literacy in AI

The sustainable and ethical integration of AI into education cannot depend solely on individual teacher efforts. It requires a solid institutional framework to guide practices, ensure equity, and promote critical literacy at the systemic level (UNESCO, 2023).

Education policies on AI must address three fundamental areas:

1. Ethical regulation,
2. Teacher training, and
3. Technological equity.

*1. Ethical regulation:*

Institutions must establish clear guidelines on the acceptable use of AI in educational contexts. This includes defining what types of assistance are valid in assessments, how to cite algorithmic intervention, and what practices constitute digital plagiarism. In addition, policies should promote respect for student privacy and data protection, ensuring that interaction with AI systems does not compromise sensitive information (Bender et al., 2021).

Ethical frameworks, such as those proposed by UNESCO (2021) or the European Commission (2022), recommend adopting principles of transparency, accountability, and algorithmic fairness. In the Latin American context, this also means ensuring that the tools used respond to local cultural and linguistic realities and avoid reliance on systems designed with Anglo-centric biases.

*2. Teacher training:*

Education policies must invest in ongoing training programs that strengthen teachers' digital and pedagogical skills. As Mishra and Koehler (2006) argue, technological, pedagogical, and disciplinary knowledge (TPACK) is key to integrating AI meaningfully.

These training courses should not be limited to technical workshops, but should also include modules on digital ethics, *prompt* design, AI evaluation, and bias analysis. Teachers need spaces for collective reflection—communities of practice, forums, educational laboratories—where they can share experiences and build situated knowledge (Wenger, 1998).

*3. Technological equity:*

One of the most significant risks of AI-based education is widening the digital divide. Policies must ensure equitable access to technological resources, infrastructure, and connectivity, preventing algorithmic literacy from becoming a privilege reserved for specific sectors. Educational AI must be designed and implemented with a social justice perspective that promotes the inclusion and participation of all students, especially those in vulnerable contexts (Selwyn, 2019).

Likewise, institutions must encourage research on AI and education to generate locally and contextually relevant knowledge. Universities, for example, can establish observatories of ethics and educational innovation to analyze the impact of AI on teaching and to produce guidelines adapted to their sociocultural realities.

**Summary of Section 3**

Artificial intelligence is redefining not only the act of writing, but also the ways of teaching, assessing, and legislating in contemporary education. *Prompting* is emerging as a new linguistic-pedagogical skill that combines critical thinking and communicative design; ethics and assessment demand transparency, accountability, and reflection; and institutional policies must guarantee an equitable, inclusive, and humanistic framework.

Critical literacy in AI is not about mastering tools, but about educating individuals who are aware of the power and limitations of algorithms. Education must teach 21st-century citizens to ask better questions, think independently, and coexist ethically with the intelligence they themselves have created. Only then will it be possible to build a genuinely democratic digital culture, where technology amplifies human intelligence without replacing it.

## SECTION 4. LOOKING TO THE FUTURE

### 4.1. The new teaching literacy: teaching with intelligence, not fear

The emergence of artificial intelligence (AI) in education has generated equal amounts of enthusiasm and fear. Some see it as a threat that jeopardizes authorship, assessment, and the authenticity of learning; others celebrate it as an opportunity to personalize teaching and democratize knowledge. Between these two positions, an urgent challenge emerges: building a new teaching literacy that allows teachers to teach with intelligence—based on understanding, ethics, and creativity—rather than fear.

The new teacher literacy involves teaching with intelligence rather than fear, taking advantage of opportunities offered by AI to enhance teaching and learning, and promoting critical and ethical skills (Floridi, 2023; Nussbaum, 2021).

This literacy is not limited to acquiring technical skills, but involves a cultural and epistemological transformation of the teaching role. The 21st-century teacher is not a transmitter of information, but a designer of cognitive experiences, a mediator between humans and algorithms, and an ethical reference point in the face of digital complexity (Fullan, 2021; Luckin et al., 2022).

In this new educational ecosystem, teachers must master three key competencies:

1. Cognitive-digital competency: understanding how AI models work, their potential and limitations, and how to integrate them pedagogically.
2. Ethical and emotional competency: maintaining a critical relationship with technology, avoiding both uncritical dependence and conservative rejection.
3. Creative and innovative competence: using AI to enhance imagination, problem-solving, and collective knowledge building.

### 4.2. Teaching with AI: from control to support

The education of the future will be characterized by a paradigm shift: from controlling knowledge to supporting learning. Instead of “monitoring” students’ use of AI, teachers will need to teach them to use these tools judiciously, ethically, and purposefully.

AI-mediated autonomous learning redefines the time and space of education. Adaptive platforms, virtual tutors, and cognitive assistants will enable students to learn in flexible and personalized contexts. However, the role of the teacher will remain irreplaceable: only human interaction can offer empathy, moral guidance, and a sense of community.

Holmes et al. (2021) warn that the future of education will depend on teachers' ability to co-evolve with technology. This means not only adapting to new digital environments but also actively influencing their design, demanding inclusive, transparent, and culturally diverse systems.

In this context, teaching with AI requires a balance between reason and emotion. As Floridi (2023) suggests, ethical intelligence—the ability to discern good in technologically mediated contexts—will be the basis of future education. Teachers must guide students toward responsible use of AI, understanding that every interaction with a machine involves a moral decision.

For example, when faced with a student who uses ChatGPT to write an essay, the teacher of the future will not automatically punish them, but will instead accompany them in reflecting on how and why they used the tool, what they learned from the process, and how they can improve their critical thinking based on that human-algorithmic dialogue.

**4.3 Emerging scenarios for AI literacy**

The future of literacy with AI is shaping up in three major complementary scenarios: pedagogical, technological, and sociocultural.

*1. Pedagogical scenario: the classroom as a co-creation laboratory*

The classroom of the future will be a hybrid space where writing, reading, and thinking are developed in collaboration with intelligent systems. Students will become augmented authors, capable of creating, analyzing, and rewriting texts with the assistance of AI.

Literacy will cease to be an individual skill and become a collaborative social practice (Gee, 2015). Educational projects will integrate audiovisual production, digital narratives, and multimodal communication, combining human creativity with algorithmic efficiency.

In this scenario, teachers will act as curators of knowledge. Their task will be to select tools, contextualize information, and guide dialogue between multiple intelligences. This pedagogical co-authorship redefines the notion of academic authority, which is no longer based on mastery of knowledge, but on the ability to construct meaning together with students.

*2. Technological scenario: the teacher as a designer of cognitive experiences*

The literacy of the future will require teachers with skills in instructional design and computational thinking. Knowing how to create *prompts*, adapt materials to adaptive platforms, and evaluate interactions with AI will be everyday tasks.

However, educational technology must evolve toward more explainable, ethical, and transparent systems. According to Luckin et al. (2022), next-generation educational AI must allow users to understand why it makes certain decisions or generates specific responses. Only then can blind dependence be avoided and cognitive autonomy promoted.

In this sense, teacher training should include notions of critical algorithmic literacy, combining knowledge of language, epistemology, and digital ethics (Ng, 2021). Teachers will not be programmers, but mediators capable of translating the languages of algorithms into pedagogical language.

*3. Sociocultural scenario: learning as a humanistic practice*

New literacy with AI cannot be reduced to a technical adaptation; it must be articulated with a humanistic and socially committed vision. Education has a responsibility to train ethical, empathetic individuals who are aware of the social impact of their technological actions.

According to Nussbaum (2021), the future of education requires strengthening moral imagination and empathy as pillars of critical thinking. AI can be a means to this end, provided it is used to promote intercultural dialogue, global cooperation, and cognitive justice.

In contexts of inequality, AI literacy must also aim to close gaps and democratize access to knowledge. Public policies must guarantee infrastructure, training, and regulatory frameworks that promote the equitable and safe use of innovative technologies.

**4.4. Educational leadership and ethics of the future**

Teaching leadership in the 21st century must be based on three principles: technological wisdom, emotional intelligence, and ethical responsibility. According to Fullan (2021) and Sahlberg (2023), these principles form the basis of transformational leadership in the age of AI.

1. Technological wisdom involves understanding the potential and limitations of AI tools, not out of fascination, but out of discernment. The educational leader of the future does not adopt technologies because they are fashionable, but because of their pedagogical relevance.
2. Emotional intelligence means accompanying students and colleagues in the digital transition, recognizing the fears, resistance, and challenges that change entails.
3. Ethical responsibility means ensuring that AI use respects human dignity, privacy, and cognitive justice.

Ethical leadership will ultimately be the axis that determines the course of future education. Teachers must become guardians of meaning in an era where data and algorithms threaten to replace reflection.

To this end, continuing education will be essential. Universities, ministries, and international organizations must promote professional development programs for teachers that focus on ethical thinking, advanced digital literacy, and educational leadership with AI (OECD, 2023).

In addition, it will be crucial to foster international collaboration networks among educators, researchers, and technologists. These global communities of practice will enable the sharing of experiences, the development of joint policies, and the construction of a planetary digital ethic grounded in cooperation and sustainability.

**4.5. Towards a pedagogy of shared intelligence**

The most promising horizon for the education of the future is the development of a pedagogy of shared intelligence: a model in which AI does not replace humans, but instead collaborates with them in the construction of knowledge.

Pierre Lévy (2019) already anticipated this vision when he spoke of *collective intelligence*, a network of distributed knowledge that mutually reinforces itself. In the age of AI, this idea takes on a new dimension: collective intelligence expands into the interaction between humans and machines, forming a hybrid cognitive ecology.

In this context, teachers take on a central role: they must orchestrate the symphony between human, artificial, and social intelligence. Their mission will be to cultivate critical thinking, empathy, and creativity in an environment of algorithmic collaboration.

The *pedagogy of shared intelligence* is based on three postulates:

- Knowledge is built through interaction. AI can offer information, but the human community generates meaning.
- Technology is a means, not an end. Educational value lies in the reflective process, not in automation.
- Ethics is the foundation of learning. The literacy of the future will be ethical, or it will not be.

In short, teaching with intelligence—not fear—means recognizing AI as an ally of human thought, but also as a reminder of our moral responsibility. Education should not fear technology, but rather train individuals to use it with judgment, compassion, and purpose.

**4.6. Summary of the fear of pedagogical intelligence**

The future of literacy with AI will depend on the education system's ability to reconcile humanity and technology. The key is not to resist innovation, but to guide it ethically. Tomorrow's teachers will need to be critical thinkers, cultural mediators, and moral guides, prepared to teach how to think in a world where algorithms also write.

The new teaching literacy is not about teaching how to use tools, but about teaching how to think and create with them consciously. Educating with AI is a balancing act: harnessing its power without losing the human voice, exploring its potential without abdicating critical judgment.

As Selwyn (2023) states, the most significant risk of AI is not that it will replace teachers, but that teachers will give up thinking. Teaching intelligently means reclaiming pedagogy as a space for reflection, care, and humanity.

## CONCLUSIONS

The analysis of the four sections allows us to draw comprehensive conclusions about literacy in the age of artificial intelligence. First, writing and interacting with AI transform cultural and educational processes, consolidating AI as a co-author and tool for critical and creative learning. Second, teaching practices must be adapted to different educational levels, promoting generative literacy, ethical evaluation, and collaborative training. Third, the design of *prompts*, the detection of AI use, and the implementation of institutional policies reflect the need for an ethical, responsible, and thoughtful approach to technological integration. Finally, the future of education requires teachers who can lead with intelligence, ethics, and creativity, teaching students to think and learn with AI in a critical and humanistic way. Taken together, the sections show that 21st-century literacy is not just about technical skills, but about comprehensive competencies that combine critical thinking, ethics, creativity, and pedagogical mediation, consolidating an education where technology enhances, but does not replace, human intelligence.

This chapter shows that integrating AI into education redefines literacy, teaching practices, and the skills required. It highlights the need for critical thinking, digital ethics, and assisted creativity. Teacher training and institutional policies are essential for the responsible use of AI.

It is recommended to foster communities of practice, develop generative skills, and establish clear ethical guidelines to consolidate critical and sustainable literacy.

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## USE OF ARTIFICIAL INTELLIGENCE

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## AUTHORSHIP CONTRIBUTION

*Conceptualization:* Gaoussou Goro.

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# Digital Literacy and Teacher Training in Artificial Intelligence

## Alfabetización Digital y Formación Docente en Inteligencia Artificial

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### ABSTRACT

This study analyzes digital literacy and teacher training in artificial intelligence in higher education in Latin America and the Caribbean, with an emphasis on the Dominican Republic. It identifies gaps between the demands of the digital educational ecosystem and teacher training, highlighting structural, curricular, and pedagogical limitations. Furthermore, it reviews the main international standards for digital competencies and their suitability for teacher training from a documentary and analytical perspective, emphasizing the need to align training programs with these frameworks and integrate artificial intelligence to meet current demands. The results show that university programs insufficiently incorporate technological content and that teacher training is largely limited to instrumental aspects. The study also recognizes the urgent need to include artificial intelligence as cross-cutting competency or subject in initial teacher training. It concludes that educational change must transcend the technical paradigm to advance toward critical digital literacy, training reflective teachers capable of implementing intelligent technologies in teaching in a pedagogical, ethical, and responsible manner.

**Keywords:** Artificial Intelligence; Digital Competence; Teacher Training.

### RESUMEN

En este estudio se analiza la alfabetización digital y la formación docente en inteligencia artificial en la educación superior de América Latina y el Caribe, con énfasis en la República Dominicana. Se identifican brechas entre las demandas del ecosistema educativo digital y la formación docente, destacando limitaciones estructurales, curriculares y pedagógicas. Asimismo, se revisan los principales estándares internacionales de competencias digitales y su adecuación a la formación docente desde un enfoque documental y analítico, enfatizando la necesidad de alinear los programas formativos con estos marcos, integrando la inteligencia artificial para responder a las demandas actuales. Los resultados evidencian que los programas universitarios incorporan insuficientemente el contenido tecnológico, y que la formación docente se limita mayoritariamente a aspectos instrumentales. Asimismo, se reconoce la urgencia de incluir la inteligencia artificial como competencia transversal o asignatura d la formación docente inicial. Se concluye que el cambio educativo debe trascender el paradigma técnico para avanzar hacia una alfabetización digital crítica, formando docentes reflexivos capaces de implementar tecnologías inteligentes en la enseñanza de manera pedagógica, ética y responsable.

**Palabras clave:** Inteligencia Artificial; Competencia Digital, Formación de Docente.

## INTRODUCTION

Today, digitization is an unprecedented phenomenon, with emerging technologies, including artificial intelligence (AI), rapidly defining social, economic, and educational spheres (Martínez, 2025). In this ecosystem, digital literacy is no longer a supporting skill but has become a key component of human development. However, there is a worrying disconnect between the pace of technological growth and educational institutions' ability to implement these technologies critically and effectively (Andion, 2021).

Digital illiteracy or ignorance is common; authors such as Toscano et al. (2025) argue that this problem constitutes a significant obstacle to educational quality because educators lack training or motivation. The Dominican context is no exception; it has particularities that hinder the comprehensive and educational development of society. This society is experiencing gradual growth in the digital age; however, there are inequalities in technological access, which contribute to the development of teacher training programs in Higher Education Institutions [HEIs] (Díaz-Moreta, 2025).

Consequently, the enigmatic body is found in the classrooms of HEIs, which are directly faced with the enormous challenge of educating competent trainers in digital tools, not only to use them, but also to conceptually and pragmatically grasp the inherent principles of Information and Communication Technologies (ICT), AI, Robotics, augmented reality (AR), virtual reality, among other emerging technologies, which encourages the creation of responsible digital citizenship (Estrada and Bennasar, 2021; Acevedo et al., 2022; Pérez and González, 2024).

It is worth noting a critical digital training gap in Dominican education in the 21st century, as teachers lack the skills and the appropriate environment to train schoolchildren who can enter the labor market demanded by this IT and technological boom. Writings such as those by Vizuete et al. (2025) establish that soft skills combined with emerging technologies are fundamental to the labor-market integration of students graduating from the pre-university system; therefore, teachers in training must be able to transmit this technological knowledge to promote cross-cutting, practical development in their students.

The purpose of this paper is to analyze digital literacy and teacher training in artificial intelligence, taking into account three complementary dimensions: digital literacy as a necessary skill for contemporary educational practice; the state of digital literacy and the development of artificial intelligence skills in Latin America and the Caribbean, with a focus on regional advances and challenges; and an analysis of teacher training programs in Latin America and the Caribbean, with an emphasis on the Dominican Republic, from a technological perspective in order to identify gaps, opportunities, and institutional strategies that strengthen teacher preparation for the demands of the digital educational ecosystem.

## DEVELOPMENT

### DIGITAL LITERACY AND TEACHER TRAINING IN ARTIFICIAL INTELLIGENCE

The advent of artificial intelligence [AI] has triggered social and economic change, reshaping the essential skills needed for active citizenship and employability (United Nations Educational, Scientific and Cultural Organization [UNESCO], 2021). In this scenario, digital literacy has gone beyond its original definition as a simple technical skill to encompass critical data curation and algorithmic reasoning. Globally, society is rapidly moving toward a media ecology dominated by intelligent systems, which are shaping information consumption, knowledge production, and decision-making. However, this rapid progress has revealed a notable gap between the demands of a digitalized society and the training provided by teacher education programs (Molina et al., 2024).

The access gap (lack of connectivity or devices) has been the primary concern in education throughout history. Although this inequality persists, especially in vulnerable contexts (Economic Commission for Latin America and the Caribbean [ECLAC], 2024), artificial intelligence has introduced a more complex dimension: the critical skills gap. AI can replicate and extend racial, socioeconomic, or gender biases already present in society, given that it operates on large volumes of data (Alonso, 2023). Likewise, this data provides knowledge at the speed of a click, enabling autonomous learning, which favors the teaching-learning process; it also promotes research and self-taught cognition when used ethically and responsibly (Solano et al., 2024).

Initial teacher training programs often show institutional inertia that contrasts with the speed of technological innovation. Currently, curricula tend to prioritize an instrumental perspective on technology, covering only introductory office automation courses or the use of general platforms and learning management systems (Calderón et al., 2025). This superficial perspective creates a disconnect between academic content and the circumstances of the post-AI classroom, where students already use generative AI tools for research, writing, and problem-solving.

To close this gap, it is necessary to review the paradigm of teacher training, both initial and continuing. AI should be considered not only as a tool for improving administrative efficiency or providing content, but also as a mechanism for equity when applied intentionally (UNESCO, 2021). This requires initial teacher training programs to incorporate teaching of: a) pedagogical prompt engineering, i.e., the ability to interact with artificial intelligence models to produce high-quality educational content; b) assessment of the authenticity of AI-generated work; and c) establishment of an ethical framework to guide how student data is used and how algorithmic transparency is ensured.

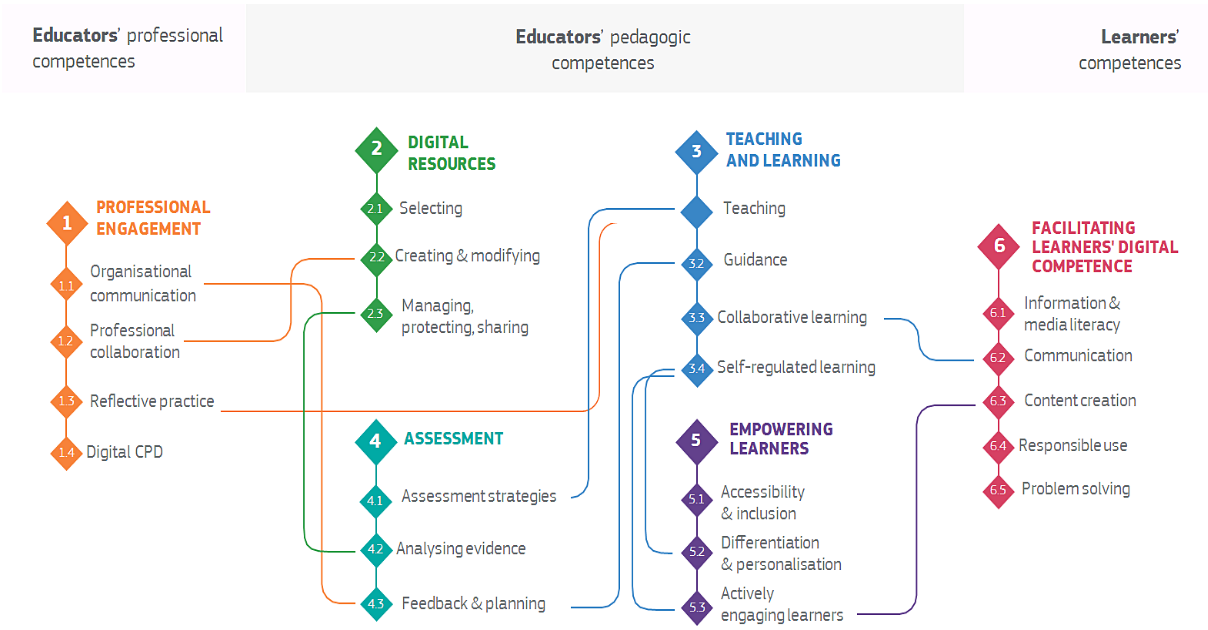
To address curriculum dissonance from a structural standpoint, it is essential to review the digital competency frameworks that underpin initial teacher education and continuing professional development. Some of the current frameworks were designed before generative AI expanded massively. Therefore, they do not address essential topics such as algorithmic citizenship, algorithmic ethics, or applied artificial intelligence (UNESCO, 2021). These frameworks must shift from a focus on software use to an approach that emphasizes adaptation, critical evaluation, and co-creation between humans and artificial intelligence during the teaching and learning process.

**Teacher's digital literacy**

Digital literacy is a process focused on acquiring knowledge and skills for the proper use of technological tools (Quispe & Visloa, 2022). It includes the ability to access, manage, understand, integrate, communicate, evaluate, and create information, as well as media literacy, information literacy, and ICT literacy, designed to help people develop a critical mindset regarding the use of digital and information technologies (UNESCO, 2025).

In the field of education, digital literacy for teachers currently includes four fundamental aspects: critical information management, data ethics and security, and the pedagogical and creative use of technology. As society becomes increasingly digitized, incorporating artificial intelligence in various areas, teacher training programs are not updating their content with the same depth or speed. Teacher training focuses on basic technical skills, but does not address pedagogical and critical issues related to AI. Resistance to change, limited institutional support, and disparities in access to technology create a gap that particularly affects rural and vulnerable populations (Dilling et al., 2024; Pita-Briones et al., 2025). This gap means that teachers are not fully equipped to meet the educational demands of a digitalized society.

In this regard, digital teaching competencies are outlined in reference frameworks developed by European and international groups to enhance teachers' technological skills in the digital age. These frameworks are guidelines that define the skills required to succeed in a specific position or field; they also guide professional development and performance evaluation. In this vein, the DigCompEdu framework offers a comprehensive reference for educators' digital competencies across six key areas, as presented in figure 2.1: professional engagement, digital content creation, teaching and learning, assessment, learner autonomy, and digital competency development (UNESCO, 2019; Pita-Briones et al., 2025).




**Note:** This figure represents the six areas included in the DigCompEdu reference framework. Taken from *the European Framework for Digital Competence for Educators: DigCompEdu* (p. 8), by Redecker (2020).

**Figure 2.1.** DigCompEdu Digital Competence Reference Framework

These areas range from Professional Engagement (use of technology for collaboration and continuous development) and Digital Content Management (curation, production, and respect for copyright) to core applications in teaching and learning (designing enriching experiences). In addition, they extend to the dimensions of assessment (use of data to modify teaching), student empowerment (inclusion, personalization, and digital well-being), and conclude with the development of students' digital competence (direct instruction of digital and critical skills), ensuring that teachers can approach technologies from a comprehensive and pedagogical perspective. According to Pita-Briones et al. (2025), in Latin America, only a small percentage of teachers adequately achieve these competencies, demonstrating the existing gap.

**Table 2.1.** Reference Framework for Digital Competencies according to UNESCO

| **Area** | **Knowledge acquisition** | **Deepening of knowledge** | **Knowledge creation** |
|---|---|---|---|
| Understanding the role of ICT in education | Knowledge of policies | Policy implementation | Policy innovation |
| Curriculum and assessment | Basic knowledge | Application of knowledge | Knowledge society skills |
| Pedagogy | ICT-enhanced teaching | Complex problem solving | Self-management |
| Application of digital skills | Application | Infusion | Transformation |
| Organization and administration | Standard classroom | Collaborative groups | Learning organizations |
| Professional learning for teachers | Digital literacy | Networking | Teachers as innovators |

**Note:** This table shows information on the areas included in the digital competency reference framework. Taken from *the ICT Competency Framework for Teachers* (p. 8), by UNESCO (2019).

Nowadays, it is not enough for teachers to be skilled in the technical or instrumental use of digital tools. The educational requirements for the 21st century demand a more critical and deeper understanding of technology, in which digital skills must be combined with ethics, reflective capacity, and creativity on the part of teachers (UNESCO, 2019; Pita-Briones et al., 2025). In this context, the DigCompEdu Reference Framework and UNESCO's proposals are a starting point, not an end goal.

This is because rapid technological transformations, especially those related to artificial intelligence, require continuous renewal of pedagogical knowledge and methods.

It is not enough to incorporate technologies into education; it is also necessary to understand how algorithms, data, and intelligent systems affect or benefit educational equity, the learning process, and pedagogical decisions. In this scenario, essential skills such as AI-mediated learning, people-centered thinking, and AI-assisted pedagogy emerge, promoting a more responsible and context-adapted education.

Thus, today's educators must move from functional digital competence to transformative digital competence.

This requires a good command of the technological foundations and an understanding of the social and ethical consequences of using intelligent systems in education. As Pita-Briones et al. (2025) point out, in Latin America, there is a notable lack of teacher preparation to address these challenges, which requires adapting training programs and continuing professional development policies that include artificial intelligence literacy as a key element in teacher training. In this regard, table 2.2 presents UNESCO's competency framework for teacher training in AI.

This global UNESCO tool was developed based on the principles of protecting teachers' rights, strengthening human capacity for action, and promoting educational sustainability. Its purpose is to guide the design of national and international competency frameworks, teacher training programs, and assessment parameters that enable educators to integrate artificial intelligence into their teaching practices in an ethical, critical, and sustainable manner (UNESCO, 2025).

This proposed set of dimensions is a significant expansion of the concept of digital teaching competency, encompassing specific skills for an educational environment increasingly shaped by artificial intelligence.

**Table 2.2.** AI Competency Framework for Teachers

| Dimension | Description | Levels of progression |
|---|---|---|
| Human-centered thinking | Focus on social responsibility, accountability, and human behavior. | Acquire, deepen, create |
| AI ethics | Applying principles of transparency, privacy, fairness, and bias prevention in the educational use of AI. | |
| Fundamentals and applications of AI | Basic and advanced understanding of how AI works for its contextualized pedagogical application. | |
| Pedagogy of AI | Design and implementation of active and personalized teaching strategies supported by intelligent technologies. | |
| AI for professional learning | Use of AI for self-training, continuous assessment, and participation in collaborative teaching communities. | |

*Note:* This table shows information on the areas included in the AI competency framework for teachers. Taken from *the AI Competency Framework for Teachers,* by Miao & Cukurova, UNESCO (2024).

The dimension of human-centered thinking requires, first and foremost, that teachers consistently place the individual, rather than technology, at the center of the entire educational process. This involves promoting social responsibility, accountability, and an understanding of human behavior in contexts mediated by artificial intelligence. From this perspective, the ethics of artificial intelligence require educators to understand and implement principles such as transparency, privacy, equity, and the prevention of bias when using intelligent tools.

This becomes crucial in an era when algorithms can reproduce inequalities or manipulate sensitive information about teachers and students.

The fundamentals and applications dimension of AI, on the other hand, aims to help teachers understand how intelligent systems work, from their conceptual basis to their practical application.

AI pedagogy involves creating teaching strategies that are active, adaptive, and personalized, supported by intelligent technologies that analyze learning data and provide feedback tailored to each student's needs. Finally, the AI for professional learning dimension encourages the use of these technologies so that teachers can train themselves, continually evaluate their performance, and participate in collaborative communities of practice, thereby contributing to sustained professional development.

Taken together, these dimensions suggest an evolutionary model that involves teachers' use, understanding, evaluation, and critical application of artificial intelligence, thereby ensuring that the incorporation of AI in education aligns with human principles and a transformative pedagogical purpose.

**State of digital literacy and AI skills development in Latin America and the Caribbean**

Digital literacy and the development of artificial intelligence skills have become essential elements for educational and social transformation in Latin America. Although some countries have made progress, the area is still grappling with significant gaps that prevent everyone from having a fair opportunity to learn and participate in the global digital market (UNESCO, 2019; Pita-Briones et al., 2025).

A recent study found that Chile and Colombia are leaders in university digital skills, but Ecuador lags behind five other countries (Martínez, 2023). According to Softtek's 2024 report, Argentina leads the region with a digital literacy rate of 66 %, while Brazil is close to 46 % and Mexico trails at approximately 37 %. Digital literacy is not just about using technology; it is about knowing how to find, check, and do. It is a key skill that helps people get involved and empowers them in society (OEI, 2024).

In the Latin American context, the incorporation of artificial intelligence into education systems is progressing unevenly. A report by Herrera et al. (2025), prepared by the Economic Commission for Latin America and the Caribbean [ECLAC], indicates that the region accounts for about 14 % of global visits to AI solutions, despite concentrating only 11 % of Internet users worldwide (Herrera et al., 2025). However, the distribution is heterogeneous: countries such as Chile, Brazil, and Uruguay are in the “pioneer” category, with more than 60 points on the 2024 Latin American Artificial Intelligence Index (ILIA). On this index, Chile scored 74,3 points in human talent specialized in AI, Uruguay 62,1, and Costa Rica 46,9. In Brazil, there was also a 282 % increase in enrollment in AI generation courses over the last year, placing it second in the region in this indicator (Herrera et al., 2025; Ti Inside, 2025).

For decades, the Dominican Republic has faced countless challenges in digital literacy, especially in the business and education sectors. In this regard, Robles et al. (2025) have identified notable deficiencies in advanced digital skills, particularly in technical and operational professions.

The education system also faces difficulties, and Gallur and Diaz (2023) note that although students and teachers recognize the importance of digital skills, 95,6 % of students believe teachers need more robust training despite advances in digital infrastructure, such as the increase in the number of Internet users, Serrano and Llorente (2023) state that teachers tend to perceive their digital skills as intermediate, especially in the fields of science and technology.

In the current Dominican context, advances in digital literacy and AI integration show both achievements and persistent challenges. A United Nations Development Program (UNDP) study reports that 68,9 % of Dominican citizens use artificial intelligence more than once a week.

**Table 2.3.** Indicators of digital literacy and artificial intelligence in the Dominican Republic

| Indicator | Result | Source |
|---|---|---|
| Students who consider teachers’ digital training to be insufficient | 95,6 | Gallur & Diaz (2023) |
| Citizens who use AI at least once a week | 68,9 | United Nations Development Program [UNDP] (2025) |
| Teachers with intermediate perception of digital skills | 63,4 | Serrano & Llorente (2023) |
| Devices delivered to students with faults | 76,6 | UNESCO, UNDP & EDUCA (2023) |
| Rural schools without connectivity | 36,7 | UNESCO, UNDP & Business Action for Education [EDUCE], (2023). |
| Goal of the “Soy Digital” program (people to be trained) | 100 000 | Dominican Telecommunications Institute [INDOTEL] & Ministry of Education of the Dominican Republic [MINERD], (2025). |

**Note:** Prepared internally based on the cited sources.

This shows significant adaptation to emerging technologies and an optimistic attitude toward their educational and employment potential (UNDP, 2025). In addition, the Dominican Telecommunications Institute (INDOTEL) and the Ministry of Education (MINERD) launched the "Soy Digital" initiative to teach 100 000 parents and guardians the basics of digital skills. However, the school system faces some major obstacles: a study by UNESCO, UNDP, and Educa (2023) found that 76,6 % of the devices given to children did not work, and that 36,7 % of schools lacked connectivity, compared to 18,1 % in urban areas.

These data reflect an ambivalent situation: on the one hand, a progressive expansion of public policies and citizen adoption of emerging technologies; on the other, a significant gap in advanced skills, equitable access, and the sustainability of digital literacy programs. Consequently, it is necessary to strengthen national teacher-training policies and to create digital ecosystems that promote the critical, ethical, and pedagogical integration of artificial intelligence.

**Analysis of teacher training programs in the Dominican Republic: From a technological perspective**

An important factor in the technological analysis of teacher training programs in the Dominican Republic is the inclusion of technology-related courses in university curricula. In this regard, Table 5 shows how five (5) higher education institutions, whose names are withheld for ethical reasons, have incorporated content related to computer science, digital skills, and educational technology. This analysis is based on the total number of credits required to obtain a teaching degree, the number of technology-related courses, and their equivalence in academic load.

**Table 2.4.** Curriculum of Dominican universities that include technology-related subjects

| Universities | Total number of credits | Specific technology subjects | Credits in educational technology |
|---|---|---|---|
| University A | 165 | - Educational Technology I<br>- Educational Technology II<br>- Technology Integration Laboratory | 9 (5,5 %) |
| University B | 172 | - Technology Applied to Education<br>- Educational Informatics | 6 (3,5 %) |
| University C | 128 | - Educational Technology<br>- Digital Materials Design<br>- Integration of ICT in the Classroom | 8 (6,3 %) |
| University D | 150 | - Educational Technology<br>- Computer Science for Educators | 6 (4,0 %) |
| University E | 140 | - Fundamentals of Educational Technology<br>- Instructional Design and Technology<br>- Assessment with ICT | 10 (7,1 %) |

The data collected show that although all institutions incorporate technology courses into their study programs, there are significant discrepancies in the approaches and depth with which they are taught. On the one hand, there are notable fluctuations in the number of credits assigned to this area: between 6 (3,5 %) at University B and 10 (7,1 %) at University E. On the other hand, the names of the courses reveal different educational perspectives, ranging from more technical approaches, such as "Educational Informatics," to more comprehensive approaches, such as "Assessment with ICT" or "Technology Integration Laboratory."

This curriculum study enables the identification of areas for improvement and strengths in the digital training of future teachers. Some universities, such as A, C, and E, provide a well-defined structure with three specific courses. Others, however, offer a more traditional model with only two subjects.

The variety of classes and different credit percentages shows that, although there is consensus on the importance of educational technology, it has not yet been standardized in teacher training programs in the Dominican Republic.

In line with this, authors of the stature of Tapia et al. (2020) advocate the incorporation of ICT as an essential discipline in training programs, since the same study conducted between 2012 and 2018 showed that the increase in technology subjects in the Republic of Chile according to the teacher training program and disciplinary teacher training (by area) was 12 % in the former and 29 % in the latter. Similarly, in the paper by Cabello et al. (2020), also conducted in Chile, the findings show that more teacher training plans do not integrate ICT (35,1 %) than those that do (22,7 %); Therefore, both authors agree that there should be government education policies to improve training programs that encourage graduates to develop technological skills in line with the digitalization of this era.

Ultimately, teacher training goes beyond preparing teachers in the instrumental use of digital platforms. The real challenge is to train educators with the sensitivity and criteria necessary to accompany their students in a reality where AI is constantly redefining the limits of knowledge. This preparation involves, above all, developing an ethical compass to guide both their teaching practice and the civic education of new generations in these essential skills.

## CONCLUSIONS

The analytical journey undertaken reveals a central paradox in contemporary teacher training, leading us to conclude that, while artificial intelligence is redefining educational ecosystems at unprecedented speed, training models remain anchored in instrumental logics that are notoriously insufficient. The theoretical foundation suggests that overcoming this dissonance requires transcending mere technical training to embrace a radically humanizing approach, where technology is understood as a space for cultural negotiation and civic practice.

In the age of artificial intelligence, teacher training must go beyond the development of traditional digital skills and include essential components such as data management, critical thinking, creativity, and the ability to supervise and support educational processes with intelligent tools. This training must be continuous, contextualized, and focused on overcoming resistance to change to ensure the successful integration of AI in education.

A pending challenge is to delve deeper into the experiential dimension of teachers, those intimate narratives of resistance, adaptation, and creative reappropriation that arise in their technological immersion, particularly in contexts of diversity and education. This limitation points to a fertile path for future qualitative research. The conclusion is that true transformation lies not in focusing on producing teachers who operate digital tools, but in training educators with the critical lucidity to question their underlying logic and the pedagogical sensitivity to use them in the construction of more inclusive and democratic classrooms.

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# Chapter 03 / Capítulo 03

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# Planning to Think with AI: The 5E Model as a Framework for Developing Soft-Skills Development and Reflective Teacher Practices

## Planificar para pensar con IA: el modelo 5E como marco para desarrollar habilidades blandas y escritura docente reflexiva

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### ABSTRACT

The purpose of this paper is to analyze the integration of Generative AI (GenAI) into the design, planning, and teaching of soft skills through the 5E learning cycle (BSCS 5E Model). The motivation for this proposal is to offer an alternative to the cognitive and pedagogical challenges, while also addressing the ethical considerations inherent in using GenAI in writing processes. Consequently, the objective is the design and documentation of a didactic unit utilizing the 5E method—Engage, Explore, Explain, Elaborate, Evaluate, which integrates GenAI education, reflective writing by educators, and authentic formative assessment. The educational intervention employed is backward design, with clearly formulated, specific, and measurable learning objectives. This approach ensures that the final product created by students is aligned with the planned outcomes; examples include metacognitive journals, critical analysis sheets, personal improvement plans, and empathetic feedback, all while incorporating the transparent use of GenAI tools.

The primary effects observed were the use and strengthening of self-reflection, an improvement in the quality of written argumentation, greater ethical awareness regarding the uses of GenAI, and the proper citation of sources. In conclusion, the 5E cycle provides a robust framework for integrating AI without replacing the educator. However, this requires transparency, clear assessment criteria, and the ongoing training of teaching staff in emerging digital literacy and the ethics of GenAI use.

**Keywords:** Artificial Intelligence; Digital Literacy; Ethics; Soft Skills; The 5E Learning Cycle (BSCS Model); Education With Artificial Intelligence.

### RESUMEN

El propósito de este trabajo es analizar la incorporación de la IAGen en los procesos de diseño, planificación y enseñanza de habilidades blandas mediante el ciclo de aprendizaje 5E (BSCS 5E). La motivación de esta propuesta es brindar una alternativa a los retos de carácter cognitivo y pedagógico, sin olvidar de los aspectos éticos que sugiere el utilizar la IAGen en procesos de escritura definiendo de esta forma que el objetivo es el diseño y documentación de una unidad didáctica con el método 5E: Engage, Explore, Explain, Elaborate, Evaluate, que une la enseñanza en IAGen, la escritura reflexiva por parte del profesorado y la evaluación formativa real. La intervención educativa utilizada es el diseño inverso, con objetivos de aprendizaje claramente formulados de modo concreto y medibles, buscando que el producto realizado por los estudiantes esté alineado con lo propuesto en la planeación, por ejemplo, diarios metacognitivos, fichas críticas, planes de mejora personal y retroalimentación empática, incorporando el uso transparente de herramientas IAGen. Los principales efectos observados fueron el uso y fortalecimiento de la autorreflexión, mejora en la calidad de la argumentación escrita, mayor conciencia ética sobre los usos de la IAGen y la citación de fuentes. A modo de conclusión, el ciclo de las 5E ofrece un marco sólido para integrar la IAGen sin sustituir al docente, pero esto requiere transparencia, los criterios de evaluación claros y la formación continua del cuerpo docente en la alfabetización digital emergente y la ética del uso de la IAGen.

**Palabras clave:** Inteligencia Artificial; Alfabetización Digital Emergente; Ciclo de Aprendizaje 5E (5E Modelo BSCS); Ética; Habilidades Blandas; Educación con IA.

## INTRODUCTION

This paper analyzes the challenges and opportunities of integrating Generative Artificial Intelligence (GAI) into the teaching of soft skills using the 5E instructional model. It is assumed that GAI not only mediates access to information but also participates in the co-production of ideas, blurring the boundary between searching, writing, and evaluating texts. This cognitive shift reconfigures pedagogical practice and academic writing by requiring students and teachers to adopt new forms of metacognition, critical evaluation of evidence, and ethical criteria for use, especially in contexts where authorship, originality, and transparency become substantive issues (Holmes, Bialik, & Fadel, 2019; Selwyn, 2024; UNESCO, 2024).

It is also recognized that teaching soft skills, such as critical thinking, assertive communication, empathy, collaborative work, academic self-regulation, and ethics, to name a few, requires sustained active experiences with opportunities for dialogue, feedback, and transfer to authentic situations. In this framework, IAGen-mediated environments are not approached as ends in themselves, but as cognitive and textual mediations that expand the repertoire of teaching practices, provided they are articulated with coherent curriculum designs and formative assessment (Bybee, 2015; Bastida-Bastida, 2019). From this perspective, IAGen does not replace the work of the professional but instead requires redefining the teaching role toward the design of experiences, the selection and organization of content, the coordination and management of academic discourse, and, finally, the ethical mediation of decisions.

## DEVELOPMENT

### ENGAGE: THE EMPTY MIRROR

To understand how the ethical and intellectual conflicts arising from this change translate into educational practice, a realistic scenario involving a university student is presented.

Pamela, who is at the end of the semester, faces a task that will determine whether she passes her course: writing a critical article on the “Challenges of authentic assessment in the contemporary educational context.” She is short on time and feels much pressure due to complex responsibilities, so she decides to use an IAGen tool. She decides to write a simple prompt that she considers proper: “Write a 2,500-word critical article on the challenges of authentic assessment in the contemporary educational context.”

In a matter of seconds, she obtains a text that is perfect in form: *“Authentic assessment is presented in contemporary education as a fundamental pillar for evaluating meaningful learning in students, transcending archaic standardized methods. Among its main challenges* *are the difficulty of implementing it at scale, the required teacher training, and the subjectivity inherent in its assessment criteria. However, overcoming these obstacles is imperative to align assessment with 21st-century skills..."* (DeepSeek, 2025)[1]

Upon reading, one notices the text's coherence, impersonal language, correct use of academic vocabulary, precision in terminology, and logical structure of ideas. In short, Pamela feels relieved because she believes she has met the essay's requirements. However, is this essay really a critical reflection? What role does critical thinking play in the face of an intelligence that does not understand what it produces? What does it mean to learn and write in the age of AI?

Situations such as the one described above reflect an emerging trend. The review conducted by Lo (2023) points out that one of the most common uses of IAGen in higher education is content generation; however, the author notes a lack of critical analysis of learning and of research providing explicit details on the real impact of IAGen on educational processes. The real problem is not the use of IAGen, but instead its unreflective use and passive attitude toward its content. The text generated by IAGen for Pamela functions as an empty mirror: it returns a generic image of the topic, but it cannot reflect the writer's experiences, doubts, ethical conflicts, critical thinking, or unique voice. Recent literature shows growing concern about ethics and underscores the urgency of guiding students on their own behavior, academic honesty, and the ethical use of AI (Chan, 2023).

However, this articulation between soft skills and artificial intelligence is far from automatic and is fraught with risks.  Pamela's situation is not an isolated event, but rather a symptom of greater challenges. These challenges were mentioned by Selwyn (2024), who argues that the publicity surrounding AI has created "difficulties in engaging in balanced and reasoned discussions" about its social implications (p. 3), leading education to a point where the urgency to adopt the technology is overshadowing an essential reflection on its nature and limits.

This observation by Selwyn (2024) is paramount: educational IAGen is not magic, but a complex statistical procedure, "mathematics, data, and computer programming, performed by humans" (p. 4). Dispelling this myth is the first step in understanding why the link between IAGen and the development of soft skills is far from automatic and fraught with risks. If AI does not "understand" what it produces (Selwyn, 2024, p. 4), but instead assembles text based on probabilities, it cannot, on its own, foster genuine critical thinking or creativity. On the contrary, its statistical logic can reinforce existing biases and translate into forms of unequal distribution of educational opportunities, reproducing dynamics of exclusion (Selwyn, 2024, p. 6) and requiring students and teachers to adapt to its limitations, in a phenomenon of "reverse adaptation" (Selwyn, 2024, p. 8). Ultimately, this brings us to the central assertion that Selwyn recovers from McQuillan: "Who has the opportunity to shape IAG becomes a question of power" (McQuillan, 2023, cited by Selwyn, 2024, p. 13).

## EXPLORE: CONVERGENT TRANSFORMATIONS AND THE IMPERATIVE OF LITERACY

Returning to Pamela's case, it is symptomatic of three concurrent transformations reshaping the educational landscape, as identified in recent literature (Bond et al., 2024).First, a cognitive transformation: students like Pamela require not only technical but also critical AI literacy, enabling them to discern between linguistic simulation and constructed knowledge. The review by Bond et al. (2024) highlights the urgent need for "greater ethical, methodological, and

[1]*Texto generado por herramienta de IA, DeepSeek. Sin fuentes académicas, se utiliza con fines ilustrativos.*

contextual consideration" and "interdisciplinary approaches" (p. 1) in the application of AIGen. This requires designing educational experiences that specify the limits and potential of these tools.

Second, a pedagogical transformation: the ease of access to texts generated by AIGen demands teaching models that organize sequences in which AIGen functions for dialogue and comparison, not as a final product. The predominance of "adaptive systems and personalization" (Bond et al., 2024, p. 18) in research on IAGen in higher education highlights the potential of these tools but also underscores the need for a robust pedagogical framework, such as the 5E model, to guide the activation of critical thinking.

Third, an ethical and cultural transformation: Pamela's case study highlights the urgent need to establish clear guidelines for transparency. Bond et al. (2024) identify "lack of ethical consideration" as the most frequently reported challenge in the reviews analyzed (p. 29), underscoring the need to educate on the responsible use of AI, including citation, declaration of use, and reflection on the limits of co-authorship.

The authors highlight a "call for greater ethics" (p. 33), emphasizing that "future primary research must ensure continued consideration of participant consent, data collection procedures, and data storage" (p. 33), principles that can be extrapolated to the use of AIGen in student assessmen.

We currently live in an era of converging transformations, where digitization, artificial intelligence, and other technologies do not advance in isolation but are intertwined, redefining labor markets, industries, and everyday life. Despite this, a worrying gap remains. As Long and Magerko (2020) warn, misconceptions about AIGen limit people's ability to use it, collaborate with it, and act as critical consumers of its products.  This raises the question: how can we move toward that future if we do not understand the forces that shape it? (Long and Margeko, 2020, p.1)

**EXPLAIN: IAGen LITERACY AS A CONCEPTUAL FRAMEWORK**

Given this scenario, it is not enough to implement IAGen tools; it is essential to train people in critical understanding. Long and Margeko (2020) propose an indispensable framework for this purpose. They define IAGen literacy as "a set of competencies that enables individuals to evaluate IAGen technologies critically; communicate and collaborate effectively with them; and use them as a tool online, at home, and in the workplace" (p. 2).

These authors' framework is organized into five thematic areas:

1) What is AI? Develop skills such as recognizing it, understanding intelligence, addressing its interdisciplinary nature, and distinguishing between general and narrow AI (pp. 3–4).

2) What can AIGen do? Identify its strengths and limitations, and imagine possible applications (p. 4).

3) How does IAGen work? Understand its processes of representation, decision-making, machine learning, human role, and data literacy (pp. 5–6).

4) How can AIGen be used? Critically evaluate its implications (p. 7).

5) How do people perceive IAGen? Reflect on preconceptions and programmability (p. 9).

In summary, convergent transformations will not be successful if the focus remains solely on technology and the human component is neglected. Long and Magerko's (2020) IAGen literacy framework offers guidance on building that component and ensuring conscious and ethical integration.

Investing in IAGen literacy for students and teachers is not an expense; it is a strategic investment that lays the foundation for:

- A prepared and adaptable future workforce.
- Critical and responsible citizens.
- More ethical and equitable technology adoption.

Integrating this framework at the heart of methodological strategies will enable convergent transformations not only in people, but with and for them, closing gaps and building a truly inclusive digital future.

**ELABORATE – ELABORATE TO TRANSFORM: THINKING WITH IAGen FROM THE 5E MODEL**

**The 5E model: a pedagogy for active thinking**

The learning mediation strategy known as BSCS 5E is among the most contemporary constructivist approaches. Designed by the *Biological Sciences Curriculum Study (BSCS)* and systematized by Bybee (2015), this instructional model organizes teaching into a cycle or sequence consisting of five phases: *Engage, Explore, Explain, Elaborate, and Evaluate*, which support the dynamic construction of knowledge based on experience, reflection, and active communication. More than a methodology, the 5E model is a strategy; it represents a cognitive structure that supports teachers in planning and guiding learning processes in which students activate prior knowledge, explore, and reconstruct meanings.

This model links knowledge with curiosity, motivation, and self-regulation of the learning process, in which metacognition and comprehension are applied. In this sense, the 5E cycle is cyclical and dynamic; each phase allows for the review of previous phases and integrates new experiences and perspectives. This is what has been called "opportune moments for learning" (Bybee, 2015, p. 64).

Adapting the 5E learning model to the digital context broadens pedagogical possibilities. It demonstrates that using technological tools within the 5E cycle enhances creativity and teacher reflection. It facilitates the co-construction of knowledge and formative assessment (Bastida-Bastida, 2019). The incorporation of artificial intelligence creates an environment conducive to applying the 5E model, as AIGen tools can function as mediators of cognitive processes, promoting the development of soft skills, particularly critical thinking, self-regulation of learning, creativity, and communication.

In line with UNESCO's *Guide to the Use of Generative AI in Education and Research* (2024), the adoption of the 5E model in AI-mediated environments requires ethical and critical digital literacy, with technology used to support human development rather than replace thinking. GIA can be a powerful tool to support learning, but, as Selwyn (2024) warns, its potential must be understood within the limits of human and pedagogical experience: "education cannot simply be reorganized to become machine-readable" (p. 10).

Based on this analysis, the 5E cycle offers a framework for planning strategies that think with IAGen. In other words, it is a space where technology participates in the learning process, but without replacing the voice, ethics, or creativity of human beings.

**Reflective interpretation of the 5E cycle**

As explained above, the 5E model is a methodological framework linked to the cognitive and ethical evolution of learning.

Each of its elements represents a different way of acting, thinking, and experiencing knowledge. Applied to situations involving IAGen, the cycle proposes a path that originates from curiosity and leads to higher levels, such as critical reflection, simultaneously integrating cognitive processes and social aspects.

*Engage*

This is the first phase of the 5E Cycle. *Engage* aims to spark students' interest and activate their prior knowledge through questions or experiences that provoke curiosity. When thinking about contexts with IAGen, this first stage allows us to denaturalize the automatic use of technologies, promoting critical awareness of how automated texts and responses are generated (Bastida-Bastida, 2019).

Bybee (2015) states that the purpose is to "link prior ideas and new knowledge" (p. 71). In lessons, this link can be made through ethical dilemmas or by highlighting experiences such as Pamela's, whose dependence on AIGen demonstrates a lack of critical thinking. *Engage:* This is the moment to spark interest with a question that could be: What does it mean to think for oneself in the age of artificial intelligence?

*Explorer*

It is during this phase that students can observe, explore, model, inquire, construct, propose hypotheses, and experiment with meanings through their interactions with their environment.

In IAGen-mediated teaching processes, this phase is interpreted in guided interactions with generative tools such as ChatGPT, Gemini, DeepSeek, among others. The purpose is to recognize their potential, areas for optimization, and limitations.

Bastida-Bastida (2019) indicates that guided exploration with technologies favors "greater openness and willingness on the part of teachers toward innovation" (p. 74). Students can then compare human responses with those generated by IAGen, analyze biases, or review sources. Curiosity becomes action, method. Exploring is not just about using, but rather about understanding what is being used.

*Explain*

This phase involves "reflection on the part of the student; they try to explain in their own words and use different means to do so. The teacher clarifies ideas, proposes new ideas or models, and provides feedback" (Bastida-Bastida, 2019, p. 75). Bybee (2015) defines the *Explain* phase as the moment when "learning becomes explicit" (p. 84). Now, within the framework of IAGen, it involves presenting the technological experience in academic, ethical, and human contexts. Along the same lines, students are expected to discuss aspects of authorship, originality, and reliability of the texts generated by IAGen, so that the classroom becomes a laboratory for argumentation. This phase promotes the development of soft skills that we seek to strengthen, such as critical and reflective thinking, active listening, assertive communication, and empathy.

*Elaborate*

In *Elaborate,* students put what they have learned into practice and must use scientific language (Bástida-Bástida, 2018, p. 75). Knowledge is applied and expanded, with the objective of this phase being to "extend understanding and transfer to new situations" (Bybee, 2015, p. 97).

Within the framework of IAGen, *Elaborate* seeks to integrate the elements learned to unify technological competencies with soft skills. Teachers accompany students in designing creative products and projects, where IAGen is a collaborative tool in the cognitive process and does not replace human endeavor. In this way, Pamela's experience can be reinterpreted at this stage. Her article, initially an empty mirror, with the appropriate support from the teacher, could become an opportunity for reflective learning, where ideas are contrasted, cited ethically, and constructed with her own voice.

*Evaluate*

Finally, the *Evaluate* phase extends across all stages of the 5E cycle, thereby promoting self-evaluation (Bastida-Bastida, 2019, p. 75). The purpose of this stage is to reflect on the influence of emerging technologies on comprehension and writing. The use of tools such as reflective logs, metacognitive journals, and empathetic feedback is one of the strategies consistent with the IAGen literacy proposed by UNESCO (2014), which emphasizes "responsible, transparent use for human development purposes" (p. 18).

Evaluation is not the last phase of the 5E cycle; on the contrary, it is a new way of thinking, a place where writing and self-reflection by teachers merge as an ethical practice.

The 5E teaching cycle proposes a framework for thinking with IAGen, without neglecting the essence of being human. Each of the phases described invites teachers and students to foster their cognitive autonomy and, in turn, challenges the scope of technology to enhance the soft skills that underpin the ability to learn how to learn.

From this point on, we delve deeper into the Elaborate phase, which serves as the axis that articulates reflective teaching and integrates the ethics of using IAGen in the development of soft skills.

**Elaborate: apply, create, and transform.**

As explained above, *Elaborate* is the central axis of the 5E learning model. This phase is where knowledge transcends and is resized: it is expanded, applied, and transformed to connect prior knowledge with novel situations and challenges. According to this stage, students consolidate what they have learned and test it in authentic contexts (Bybee, 2015).

In higher education, *Elaborate* marks the transition from theoretical knowledge to reflective action. At this stage of the cycle, IAGen emerges as a mediation tool that enhances more complex writing, design, and communication processes, provided that its integration is based on a solid ethical and pedagogical framework.

When the 5E model is adapted for digital tools, the elaboration phase fosters creativity, autonomy, and innovation (Bastida-Bastida, 2019, p. 75). These characteristics are consistent with the soft skills identified as essential in digital literacy and IAGen ethics: critical thinking, empathy, self-regulation, and responsibility (UNESCO, 2024; Chan, 2023).

*Elaborate* seeks to restructure thinking, which modifies the relationship between people and the technological tool. In this context, Pamela's situation takes on new meaning. What began as dependence on IAGen becomes an opportunity to rebuild authorship, recognize the limits of the tool, and cultivate her own voice.

*Elaborate with human meaning*

Developing with human meaning means understanding that artificial intelligence does not replace experience or understanding, but instead expands and strengthens them when used thoughtfully. The purpose is to enable students to use knowledge meaningfully in different contexts (Bybee, 2015). From this perspective, IAGen is incorporated as a cognitive intermediary that can expand the capacity for analysis and expression, but thinking is intrinsically human.

Selwyn (2024) warns that one current risk is the "uncritical delegation of writing and reasoning to automated systems" (p. 4). To elaborate with human meaning is to restore learning's ethical dimension, its narrative, and its emotion: that the text is not an empty mirror, but quite the opposite, an expression of the subjective and unique experience of the human being.

One option in teaching practice is to allow students to analyze a text generated by AI and reinterpret it from a personal perspective, adding nuances, examples, or analogies from their own experience or creativity. This action develops cognitive empathy, which is the ability to understand others' intentions and transform them into meaningful understanding.

*Ethical elaboration*

Ethical elaboration is conceived as the IAGen not replacing reflection, but rather provoking it. This allows for strengthening self-regulation and academic honesty, and for developing soft skills for responsible digital citizenship. Ethics becomes a daily and situated practice, not a slogan to be followed abstractly. To apply ethical elaboration, for example, students can be asked to compare two texts, one of their own and one generated by AI, in order to discuss the differences in style, argumentation, tone, and conceptual and contextual depth.

The use of AIGen in higher education requires an explicit ethical commitment. AIGen literacy must include an understanding of principles such as transparency, traceability, and respect for authorship. Ethical writing involves teaching students to declare their use of generative tools, cite correctly, and reflect on their role as co-authors (*UNESCO*, 2024).

Chan (2023) insists that the ethics of IAGen use cannot be reduced to institutional policies, but must be part of the educational process: learning to decide when, how, and for what purpose technology is used.

*Collaborative production*

According to the 5E model, the elaboration phase encourages collaboration and meaningful communication. Learning is consolidated when it is shared, discussed, and reconstructed collectively (Bybee, 2015, p. 103).

IAGen, used with pedagogical intent, can become an ally in enhancing this dimension. Building on shared meaning and recognizing human contribution as technological mediation are important for developing skills such as assertive communication, empathy, and conflict resolution. According to systematic reviews, collaborative applications of IAGen, such as digital co-writing or group idea generation, facilitate the integration of different perspectives and visions, including cognitive styles. IAGen acts as a catalyst for co-creation and reflective, collaborative work, enabling each member to analyze, correct, and improve a standard product with automated support (Garzón et al., 2025; Marzano, 2025).

Returning to Pamela's case, her situation could be transformed if, from the outset, work in pairs or groups were established in which IAGen is used as a starting point for discussion rather than a substitute for human thought. In this way, human interaction returns to the center of learning.

*Elaborate to evaluate*

Developing also involves evaluating: not in terms of grading, but in terms of metacognition and continuous improvement. Evaluation within the 5E model should be a natural part of the learning process, where students reflect on their own progress (Bybee, 2015, p. 112).

To apply this principle in the methodological strategies mediated by IAGen, formative and reflective assessment is an important part of its development, including learning logs, critical files, and personal improvement plans. These tools can be used to monitor student progress and provide effective feedback. IAGen can support this process by generating automatic observations on the coherence of texts or the diversity of arguments. However, interpretation and empathetic feedback are tasks that cannot be replaced by teachers (Bastida-Bastida, 2019).

Suppose Pamela's teacher had implemented this phase. In that case, the student might have reflected on her dependence on IAGen, understanding that the value of the article lies in her ability to think and not just to produce. In this way, assessment becomes ethical and self-critical learning, integrating IAGen into education without dehumanizing the cognitive process (UNESCO, 2024).

**Table 3.1.** Relationship between phases of the 5E model, soft skills, and integration with generative AI

| Phase of the 5E model | Cognitive-pedagogical purpose | Soft skills involved | Possible integration with GAI |
|---|---|---|---|
| Engage | Activate prior knowledge, spark curiosity | Critical thinking, intrinsic motivation | Initial dilemmas or prompts that provoke reflection on IAGen |
| Explore | Inquire and discover through interaction | Curiosity, autonomy, cognitive openness | Compare AI/human responses, detect biases or errors |
| Explain | Communicate and organize knowledge | Communication, empathy, logical reasoning | Argue with the support of AIGen, develop verified explanations. |
| Elaborate | Apply, create, and transfer knowledge | Creativity, ethics, teamwork | Design projects or essays co-authored by IAGen and humans, citing responsibly |
| Evaluate | Reflect on and self-regulate learning | Self-criticism, responsibility, self-regulation | Metacognitive logs, empathetic feedback assisted by IAGen |

Adapted from Bybee (2015), Bastida-Bastida (2019), and UNESCO (2024).

## CONCLUSION

Elaborate represents the convergence point where pedagogy and technology transform into action, driving change in the work of teachers and students. Artificial intelligence ceases to be a tool for mechanical production and becomes a means of reflective authorship, intrinsically linked to ethics and deep learning.

Teaching is much more than presenting content; it is offering structured opportunities to learn how to think. (Bybee, 2015, p. 120). Following this premise, the 5E model and IAGen literacy share a common goal: to train competent individuals to learn autonomously, ethically, and humanely in a digitally symbiotic world.

**Towards a pedagogy of reflective authorship**

The 5E model is the backbone of this chapter; it is the epistemological and pedagogical framework for rethinking teaching in the age of generative artificial intelligence. Far from being a mechanical sequence, each phase is elevated to a structure of intellectual resistance whose highest priority is critical thinking, meaningful experiences, and metacognitive reflection, ensuring that the center of pedagogical action remains the human being in the teaching-learning process.

Faced with the danger that education at its different levels will passively adapt to AIGen systems (Selwyn, 2024), the 5E model seeks to move from technological fascination and enchantment to conscious authorship. This pedagogical journey, illustrated by the evolution of Pamela's case, transforms dependence into opportunities to rethink the student's actions, to recognize the limitations of generative tools, and to enable her to develop her own voice in relation to them.

The meaningful integration of AIGen, according to UNESCO (2024) and Bastida (2019), requires enhanced reflective teaching, an approach in which technology serves as a mediator to strengthen creativity, ethics, and collaborative work. It is the teacher, as a cognitive and ethical architect, who establishes learning contexts where elaboration and evaluation become acts of liberation.

Ultimately, planning to think with IAGen requires designing environments of critical interdependence in which rejection is not an option. However, neither is dependence, nor is it a conscious relationship with technology.

Knowledge culminates in transformative actions that uphold ethical standards and foster meaningful learning. The 5E model is not linear and closed. However, it is a process of continuous growth, expanding in a spiral and reaffirming education as a permanent act of humanity, where intelligence is measured by the depth of reflection rather than the speed of response.

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3. To assist in the search for synonyms and synthesis during the planning phase.
4. To evaluate the internal consistency, spelling, punctuation, grammatical uniformity, style, and syntax of the manuscript.

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# Chapter 04 / Capítulo 04

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# Generative AI-assisted teaching strategies for designing cost structures with rigor and scalability

## Estrategias didácticas asistidas por IA generativa (IA Gen) para diseñar estructuras de costos con rigor y escalabilidad

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**ABSTRACT**

This chapter examines how to rigorously and scalably integrate generative artificial intelligence into the teaching of cost structures in higher education. The objective is to design a teaching framework and strategy architecture with *prompts* aimed at strengthening accounting reasoning, traceability, and formative assessment. An evidence-based instructional design approach is adopted that articulates active learning, supervised algorithmic tutoring, and verification protocols. Additionally, prototypes are proposed for activity-based costing, time-based extensions, and cost-volume-profit analysis, along with prompt engineering rubrics and learning outcome matrices. The findings point to significant improvements in process transparency, the relevance of assumptions, and the reasoned defense of decisions when these are based on the documentation of interactions, triangulating product, process, and calculation. It is also noted that quality depends on data curation, critical literacy, and meaningful human oversight. The implementation of responsible use policies, the creation of curriculum-aligned prompt libraries, and the development of assessment cycles with iterative feedback are recommended. The contribution lies in translating the current discussion on generative AI into operational practices that enhance the quality of learning (SDG4) and the reliability of accounting decisions.

**Keywords:** Generative Artificial Intelligence; Cost Accounting; Prompt Engineering; Activity-Based Costing; Formative Assessment.

**RESUMEN**

El capítulo examinará cómo integrar con rigurosidad y escalabilidad inteligencia artificial generativa en la enseñanza de estructuras de costos en educación superior. El objetivo parte del diseño de un marco didáctico y una arquitectura de estrategias con *prompts* orientados al fortalecimiento del razonamiento contable, la trazabilidad y la evaluación formativa. Se adopta un enfoque de diseño instruccional basado en evidencias que articulan el aprendizaje activo, la tutoría algorítmica supervisada y los protocolos de verificación. Aunado a ello, se proponen prototipos aplicados a costeo basado en actividades, extensiones basadas en tiempo y análisis costo – volumen - utilidad, junto con rúbricas de ingeniería de *prompts* y matrices de resultados de aprendizaje. Los hallazgos señalan mejoras significativas en la transparencia del proceso, en la pertinencia de los supuestos y en la defensa argumentada de decisiones cuando éstas forman parte de la documentación de las interacciones, triangulando producto, proceso y cálculo. Se advierte además que la calidad depende de la curaduría presente en los datos, la alfabetización crítica y el control humano significativo. Se recomienda la implantación de políticas de uso responsable, la generación de bibliotecas de *prompts* alineadas al currículo y el desarrollo de ciclos de evaluación con retroalimentación iterativa. El aporte radica en traducir la discusión actual sobre IA generativa a prácticas operativas que eleven la calidad del aprendizaje (ODS4) y la confiabilidad de la decisión contable.

**Palabras clave:** Inteligencia Artificial Generativa; Contabilidad de Costos; Ingeniería De *Prompts*; Costeo Basado En Actividades; Evaluación Formativa.

## INTRODUCTION

Teaching cost structures faces a sustained challenge: translating the complexity of real-world processes into the classroom without losing conceptual clarity or rigor in measurement. This is where the emergence of generative artificial intelligence (Gen AI) reconfigures this challenge by offering conversational tutoring, example generation, and immediate feedback, while also demanding critical literacy, verifiability, and authorship responsibility. In this context, the chapter aims to design and justify an AI-assisted teaching ecosystem for learning ABC costing, time-based extensions, and cost-volume-profit analysis with high standards of quality, ethics, and scalability.

García Peñalvo et al. (2024) frame the opportunities and challenges of this transition, arguing that generative AI, when integrated for explicit pedagogical purposes, can strengthen accounting reasoning by making visible the process of model construction, the choice of drivers, and the evaluation of scenarios.

This primarily requires documenting prompts, outputs, and decisions and, above all, submitting the calculation for verification with auditable traces. The quality of the interaction depends on competence in prompt engineering, which acts as a mediator between learning objectives, case study data, and output format, and must be evaluated with valid and reliable instruments (Gutiérrez Rosado et al., 2025).

The chapter is structured in four sections or guiding axes. First, a didactic framework is presented that articulates active learning, artificial intelligence (AI)-guided tutoring, and critical literacy, with operational criteria of privacy, verification, and human control. Second, an architecture is proposed that articulates strategies and prompt templates to orchestrate roles, flows, and iterations in cost tasks. Third, prototypes for ABC, TDABC, and CVU are described that perfectly exemplify how AI amplifies exploration and justification, and the criteria of rigor, evaluation, and scalability are finally discussed, which allow for the institutionalization of quality practices (Alier-Forment et al., 2025).

The relevance of this approach is supported by disciplinary evidence, as the literature on cost accounting indicates that the activity-based approach improves the allocation of inputs, the analysis of processes, and managerial decision-making when the binding causal relationship between resource consumption and cost objects is preserved (Casanova Villalba et al., 2021). This is precisely where generative AI enables rapid testing and iteration of scenarios and sensitivities without sacrificing the reasoned defense of assumptions or the reconciliation of totals, promoting the articulation of transferable learning and more informed decisions in commercial, industrial, and service contexts.

The chapter seeks to translate the general discussion on AI in higher education into an operational design for teaching cost structures, with well-defined responsibilities, robust verification protocols, and process-focused assessment. For Baldrich & Domínguez-Oller (2024), this avoids technocratic dependence and aims to achieve a level of literacy that combines an exceptional triad: technical precision, operational ethics, and disciplinary communication.

Given these precisions, academia is invited to consider the use and implementation of generative AI as a tool to make learning more transparent and accounting decision-making more robust, without ever renouncing the requirement to argue, analyze, calculate, and verify with professional judgment.

## DEVELOPMENT

### Didactic framework and principles for integrating generative AI into costs

The integration of generative AI into cost structure courses in our academic centers, from a didactic point of view, requires the articulation of learning that, beyond being active, is guided by tutorials mediated by artificial intelligence agents (AI agents) and a continuous evaluation process. However, critical literacy in AI is necessary to understand not only its much-praised capabilities but also its implicit limitations and risks, and to support solid institutional policies that guide its use from a pedagogical perspective.

Technology, and above all these tools, must be at the service of the judgment and decision-making capacity of the accounting professional, reinforcing not only the autonomy of the student, but also, as pointed out by García Peñalvo et al. (2024), evaluative transparency, which stems from the need to train teachers and students and goes hand in hand with the revision of curricula to ensure that its use is profoundly ethical and humanistic.

Pedagogically speaking, García Sánchez (2023) offers a clear synthesis of these fundamentals when he argues that generative AI is articulated with behavioral, cognitive, constructivist, and even connectivist approaches. However, this is precisely why its implementation and relevance lie in the design of meaningful experiences that connect immediate feedback with active meaning construction.

It is at this point that the role of virtual tutors comes to the fore, facilitating metacognitive scaffolding and simulations in which decisions must be made about costs, while networked platforms promote collaborative learning and evidence curation. At this point, the diversity of paradigms may require explicitly stating basic assumptions and quality criteria before delegating task performance to a model, thereby transforming early AI literacy into epistemological literacy.

Tutoring guided by artificial intelligence tools takes on real meaning when it is integrated symbiotically with practical, real-life case designs that require in-depth, structured cost analysis and professional reporting. Given this requirement, authors such as Alier-Forment et al. (2025) recommend conversational assistants incorporated into the course corpus to ensure the traceability of sources and the orientation of specific tasks, as is the case with the linking of questions and concerns that students generally present with certain course content and audiovisual material, thus strengthening validation, active learning, investigative autonomy, and the coherence of their final results.

As has been the case throughout human history, for any adoption to be considered truly responsible, a set of explicit principles must be guaranteed, such as privacy, protection of student confidentiality, algorithmic transparency, strategic alignment with the curriculum, development of transparent interfaces, and adequate teacher supervision.

To achieve this, it is also necessary to minimize the cognitive load introduced by complex tools and to ensure verification mechanisms that prevent the acceptance of speculative answers as valid. Alier-Forment et al. (2025) formulate practical guidelines throughout their research that guide this pedagogical governance of generative AI in university contexts, where the operational criteria are ultimately translated into rubrics and protocols that serve as accompaniment for each activity.

From this perspective, the mastery required in the discipline requires anchoring the framework in results specific to learning cost accounting, namely, modeling structures, analyzing situations, and the fundamentals and arguments of decision-making. From this perspective, when deploying courses with generative AI, it is necessary to require, in the words of Casanova Villalba et al. (2021), the balances and perspectives that justify this emphasis on structural cost analysis, that is, the student must argue with evidence their choice of allocation bases, the identification of activities involved, and the articulation between costs and processes, since the aim is not to automate reasoning but to strengthen it with the acquisition of fundamentals, verification, and traceability.

Da Costa Marques (2012) substantiates the contribution of ABC in university contexts, as this approach provides a robust basis for translating resource consumption into activity and product costs, a central aspect in designing prompts for the simulation of reallocation scenarios. Improving the quality of indirect cost information will directly favor process management, making it ideal for AI-guided tasks that require triangulation and critical review.

The practical relevance of the framework is strengthened by sectoral evidence obtained, for example, in logistics, where the costs associated with activities can become the second most important component after production. This situation requires modeling processes, times, and critical points before making decisions. This is where the argument put forward by Zúñiga Marín & Aguirre González (2022) becomes most relevant, when they state that generative AI supports mapping and sensitivity analysis, provided that the data and assumptions are auditable.

Segarra Ciprés et al. (2024) report these tensions and opportunities in their teaching experience in the higher education system. The authors indicate that AI literacy also involves understanding teachers' perceptions, concerns, and risks, which range from the veracity of responses to the confusion that may arise between the use of the tool and learning achievement. However, beyond latent concerns, there are recognized benefits to streamlining tasks and exploring topics, as competency mapping must integrate not only verification skills but also critical reasoning and the ethical treatment of sources, along with strategies that enable self-regulation of learning.

The development of prompt engineering competency thus becomes a cross-cutting axis for articulating disciplinary rigor with metacognition. In this regard, Gutiérrez Rosado et al. (2025) highlight the need to evaluate this competency in higher education validly and reliably. Therefore, the rubric must consider intentionality, context, restrictions, success criteria, and the traceability of sources, in addition to reflecting on the algorithmic biases and hallucinations presented by LLMs. Likewise, the teaching ecosystem must integrate microcycles of design, testing, and prompt review, with evidence commented on in the respective portfolios.

Suárez-Martínez et al. (2025), throughout their research, show an evaluative method based on prompt engineering with augmented retrieval, highlighting that the evaluation of media products and artifacts generated by AI must be based at all times on clear indicators and explainable analytics that effectively capture the quality, learning, and transmedia production when applicable (Sarmiento Contreras & Zamora Arízaga, 2025). In addition, it is relevant to use frameworks such as the GHQ (Goal Question Metric) to align objectives, questions, and metrics, always with transparency regarding training data and review procedures (2008). Thus, the rubrics used in courses should incorporate evidence of prompt iteration, along with corresponding justifications for decisions.

The coherence of the framework is supported by recent evidence reporting improvements in personalization, participation, and immediate feedback when generative AI is integrated into adaptive designs. Romani Pillpe et al. (2025) synthesize these findings and warn of the importance of AI literacy for instructional design, further emphasizing that such benefits require deeply ethical literacy, solid corpus curation, and the implementation of verification protocols to avoid accountable decisions based on opaque outputs, thus consolidating all the criteria of relevance, accuracy, traceability, and equity that are necessary to reform the critical analytical capacities of professional judgment.

**Strategy, architecture, and prompt ecosystem**

The design of a prompt ecosystem for courses that teach cost structures requires an architecture that connects learning objectives, accounting data, and pedagogical verification. It is therefore necessary to propose a procedural sequence that integrates teaching planning, conversational tutoring, and quality control, each with traceable evidence of the process (Torres & Blanco, 2023).

In addition, technological orchestration must be aligned with institutional policies and a process of progressive AI literacy, so that the tool complements and exponentially enhances professional judgment rather than replacing it. Such curricular decisions require clear frameworks for evaluation, ethics, and teacher training (García Peñalvo et al., 2024).

This is where the architecture organizes roles and flows. At the same time, the teacher designs cases, defines criteria, and validates assumptions, which is reinforced by the conversational tutor guide (AI agent), which exemplifies and suggests alternatives, using an automated verifier to check internal consistency and reconstruct calculations, so that, ultimately, the student argues and defends their solution (Torres Vargas, 2024). Consequently, Borja Borja (2025) demonstrates that personalized tutoring with AI can increase autonomy when there is a precise pedagogical design, as the interaction becomes an iterative cycle of question, answer, and refinement, with explicit goals and public rubrics, favoring personalization, motivation, and self-regulation, as long as the tutor is used as scaffolding and not as a shortcut (Suescum Coelho et al., 2025).

According to Gutiérrez Rosado et al. (2025), the technical core of the ecosystem comprises prompt templates, task contracts that specify a purpose, context, data, and the corresponding output format. This is where the quality of the prompt is evaluated first for clarity, then for completeness, data relevance, success criteria, and, above all, its traceability. It is therefore a competent approach that, by incorporating metacognition, requires justification of assumptions, forces detailed verification, and facilitates the reliable measurement of these dimensions.

For Puerto & Ruiz (20254), the operational sequence includes a pre-diagnosis that allows prior knowledge to be activated, that is, an initial prompt to generate an initial solution and a kind of guided re-prompt that ultimately improves accuracy, explainability, and consistency; the output is not reduced to the simple final result, but documents iterations and ongoing decisions.

Meza Arguello et al. (2025) point out that evidence in higher education suggests that the perceived usefulness of assistants increases when teachers teach them to refine questions and demand more auditable output formats, increasing the transparency of the learning process, which translates into significant improvements in understanding when working with guided iterations and verifiable products (Segarra Ciprés et al., 2024).

In the area of costing, prompt templates should prompt the creation of an activity dictionary, the identification of drivers, the estimation of rates, and the reconciliation between resource costs and allocated costs. This is where an effective prompt will specify the cost object, delimit processes, provide structured data, and request tables with calculation traces. For Da Costa Marques (2012), the emphasis lies precisely on explaining why an inducer is causal and how the cost varies under different scenarios. Only in this way can the quality of the decision be improved by translating resource consumption into information relevant to management (Juca et al., 2024).

For Albarracín Vanoy (2023), in logistics environments, it is helpful to have a set of templates that connect time, capacity, and transfer points to the allocation of indirect costs. In this regard, Zúñiga Marín & Aguirre González (2022) illustrate how a well-parameterized ABC allows for the identification of sources of inefficiency in supply chains, recommending that assumptions about volume, variability, and seasonality be made explicit, and, in addition, requiring sensitivity analysis with limited percentage changes, which will verify the duty to check the closure of sums and consistency between activities.

Cost-volume-profit analysis requires templates designed to structure margins, break-even points, and scenarios with simultaneous variations in price, mix, and fixed costs. That is why, at this point, the task contract must require the reporting not only of assumptions, but also the derivation of formulas and the tabular presentation of multiple scenarios, accompanied at all times by a reflection on sensitivity and risk. Casanova Villalba et al. (2021) emphasize that pedagogical value truly emerges when quantification is connected to narratives of management and continuous improvement.

The architecture outlined in the prompt requires, in Zapata Ros's (2024) words, a quality control module that translates the evaluation into verifiable evidence. In this vein, he proposes that each delivery include the version of the prompts, the assistant's output, and a human verification annex that recalculates and justifies discrepancies. This is how a verification agent can be deployed to review these tables, identify closings, and flag inconsistencies. Under this operational logic, the reliability of the process is reinforced, and co-evaluation is facilitated, a co-evaluation that not only favors replicability but also the process of meta-reflection (Suárez-Martínez et al., 2025).

Baldrich & Domínguez Oller (2024) argue that the writing dimension of the ecosystem requires transparency about AI's contributions in the corresponding reports and technical notes. Therefore, they maintain that each template used should include at least three sections: responsible authorship, citation criteria, and a statement of the assistant's limitations. In addition, it is advisable to promote cross-peer review strategies to strengthen style, consistency, and the use of evidence. Research on academic writing with conversational assistants (González, 2025) indicates gains when teaching guidance, peer review, and a strong emphasis on disciplinary argumentation are combined, without delegating epistemological responsibility.

Sustainable adoption of the ecosystem benefits from a realistic framework that not only addresses expectations but also reinforces them with training support that addresses concerns, perceptions, doubts, and risks of dependency. The architecture must, prima facie, incorporate an initial orientation, teaching contracts that are sufficiently explicit, and, above all, support mechanisms so that students with less technological familiarity are not left behind. García Sánchez (2023) notes in his research that mixed attitudes become more favorable when purposes are clarified, when guided examples are offered, and, above all, when standards of academic honesty are established, emphasizing the importance of transparency and accountability to maintain trust in evaluation processes.

The external consistency that must prevail in the ecosystem rests on the convergence of studies showing benefits from personalization, feedback, and engagement when AI is effectively integrated, with clear criteria for systematic verification (Villacreses et al., 2025). Recent reviews, such as that developed by Romani Pillpe et al. (2025), recommend moving toward evidence-based designs, with metrics aligned with learning outcomes and protocols that reduce the opacity of models. An iterative and documented approach is therefore required to facilitate educational quality assurance and scale successful experiences not only in terms of costs but also in different subjects.

Governance must be based on ethical and operational principles that protect privacy, academic integrity, and, above all, the maintenance of meaningful human control, primarily because the architecture of these prompts must limit access to or violation of sensitive data, promoting the approval and requirement of understandable explanations that guarantee that the final decision remains in human hands, that is, with the student and the teacher as facilitators of the process. It is advisable to institutionalize rubrics, protocols, and repositories of validated templates in this way, so that they evolve with practice, balancing innovation, quality, rigor, and educational responsibility. (Alier-Forment et al., 2025).

**Learning prototypes for cost structures**

This section describes educational prototypes that integrate generative AI to support learning, practice, and evaluation of the design of cost structures in commercial, industrial, and service contexts. The emphasis is on pedagogical replicability and progressive improvement through prompt engineering, so that students progress from guided tasks to autonomous and transferable performance. In this sense, it is assumed that competence in prompt design requires explicit, assessable criteria, as a flexible, adaptable rubric maintains the validity of the process in the face of rapid technological evolution and helps overcome approaches that focus solely on the final product. Gutiérrez Rosado et al. (2025) support this need and offer methodological bases for its implementation in higher education.

The prototype focuses on building an ABC model from a dataset containing indirect costs, activities, and cost objects. AI is used to suggest initial activity schemes and propose plausible drivers, which the student contrasts with evidence from the case. Consequently, a refinement cycle is promoted in which ambiguities are corrected, activities are relabeled, and drivers are justified with causality criteria. This itinerary converges with the canonical definition of ABC as a two-stage measurement and allocation method, proper not only for calculating costs but also for supporting management control and strategic decision-making. Da Costa Marques (2012) explains this by detailing the transition from resources to activities and from activities to cost objects.

As can be seen, algorithmic support is particularly fruitful when the case involves extensive activity chains, product heterogeneity, or scale variations. In this vein, a second prototype applies the ABC scheme to logistics processes, asking AI to help map key activities, estimate relative consumption, and highlight cause-and-effect relationships between drivers and tasks. A student contrasts each suggestion with observed data and contextual assumptions, reducing bias and verifying consistency.

Zúñiga Marín & Aguirre González (2022) document the relevance of this approach by emphasizing the importance of causal drivers and measuring activity consumption to obtain more reliable costs in profitability decisions. On the other hand, a third prototype is proposed to extend the analysis to standard time-based schemes, where the student formulates time equations for activities and uses AI to test scenarios of capacity, bottlenecks, and alternative allocations.

The model's function is not to replace professional judgment under any circumstances, but rather to accelerate the identification of critical assumptions and their sensitivity to variations in scale or product mix. In this way, students learn to integrate operational measurements into a cost system, with the dual purpose of achieving informational accuracy alongside decision-making discipline. Casanova Villalba et al. (2021) emphasize that rigorous cost management, supported by methods that detail items and activities, strengthens decision-making and aligns information to generate truly sustainable profits.

In addition, a fourth prototype focused on cost-volume-profit analysis is proposed. AI acts as a co-producer of scenarios by generating banks of assumptions about prices, elasticities, sales mix, and fixed and variable cost structures. At the same time, the student validates the consistency and relevance of each case. Therefore, the practice combines financial interpretation with hypothesis testing, incorporating sensitivity analysis and discussion of safety margins.

This makes it clear that the educational goal is for students to move from mere exercises that, at first glance, appear algorithmic to deeper narratives of more profound decision-making, where they can justify break-even thresholds, assess the impacts of the mix, and consider alternatives for improvement that benefit the organization. It is within this framework that cost management is inseparable from planning and evaluating results, because, as Casanova Villalba et al. (2021) argue, highlighting cost information accurately strengthens the balance between operational decisions and profitability objectives.

In prototypes, generative AI plays a tutorial role, guiding exploration step by step, offering immediate feedback, and adapting the level of scaffolding based on observed performance. For this reason, Posso-Pacheco (2025) argues that this type of interaction promotes autonomy without sacrificing methodological rigor, since each AI suggestion will require verification not only with data, but also with accounting principles.

Borja Borja (2025) emphasizes that it is precisely this personalized support that enhances retention and self-management of learning in higher education, given that algorithmic tutoring is integrated and mimics teaching mediation, reinforcing content, motivation, and self-regulation when there is clear pedagogical guidance.

The effectiveness of prototyping depends mainly on sound prompt engineering. Torrealba Dugarte (2024) recommends starting with clear contextual instructions that establish the role, the objective pursued, the output format, and the quality criteria; then iterating with requests for cross-checking, searching for counterexamples, and explanations of critical assumptions. It is through the development of this pattern that the accuracy of responses and the structure of sequential reasoning are improved, as the student, step by step, avoids giving generic answers, thereby promoting greater didactic traceability. Entering clear prompts with explicit context and constraints guides the model and yields much more valuable and relevant results in educational interaction (Segarra Ciprés et al., 2024).

The evaluation of prototypes should include a meta-communicative layer that documents objectives, representative tasks, validation of the responses generated by the system, but primarily the iterative redesign of interactions, as this is relevant in the articulation of communicative evaluability methods with the adaptive interaction factors of the prompts, so that the student themselves learns to audit and detect possible biases, errors, and deviations, taking on a much more active role and allowing them to propose improvements. Suárez-Martínez et al. (2025) describe this methodological harmonization by outlining how to make explicit the stages of preparation, implementation, validation, and feedback to ensure coherence between pedagogical intention and the results generated by AI. However, there are caveats, and adoption is not without precautions that must be considered, as evidence suggests heterogeneous student perceptions of the accuracy, usefulness, and teachers' preparedness to integrate these tools into the classroom (Mosquera-Gende & Canut, 2025). These perceptions reinforce the importance of making criteria explicit, measuring learning, and maintaining critical literacy in AI that enables responsible use. In specific educational contexts, there are disparate assessments of its suitability and accuracy, as well as doubts about the preparation teachers have received for its incorporation. This situation, in effect, requires institutional policies and continuous training (García Sánchez, 2023).

The prototypes described articulate cost modeling, algorithmic tutoring, and metacommunicative assessment to develop technical and metacognitive skills with traceability. Consequently, the emerging training ecosystem not only accelerates mastery of ABC, time-based extensions, and CVU analysis but also enables personalization and student engagement when designed with transparency and ethics. Based on this, Romani Pillpe et al. (2025) conclude that integrating generative AI into adaptive and personalized environments increases student participation, provided literacy and ethical considerations are addressed.

**Rigor, evaluation, and scalability of the ecosystem**

For García-Peñalvo (2024), the rigor that should govern generative AI-assisted learning ecosystems must be based on verifiable criteria, transparent procedures, and traceable evidence of learning. Therefore, assessment cannot be reduced to the mere mechanical or quasi-automated detection of machine-generated texts, since such detectors exhibit empirical limitations that compromise fair academic decisions (Franganillo, 2023).

It is under these considerations that it is more prudent to shift the proper focus to performance quality, to the explicitation of processes, and, above all, to consistency with the learning outcomes of the cost structures course, as this is how evaluative fairness and reputational security for students can be ensured, according to recent literature on AI in education (López De La Cruz, 2024).

Suárez-Martínez et al. (2025) point out that assessment should triangulate evidence: the final product of the task, the process of interaction with AI, and the student's own accounting reasoning. In addition, it should incorporate traces of the prompts used during the session, brief justifications, and references to the subject matter, allowing it to assess how algorithmic assistance is transformed into meaningful learning. This is where the approach is consistent with assessment experiences mediated by prompt engineering for the critical appraisal of these educational artifacts, using the simulation of expert panels with generative AI to contrast criteria, thus enriching formative feedback.

Rigor requires recognizing prompt engineering as an assessable, cross-cutting, and transferable competency. Therefore, a specific instrument, such as the prompt engineering rubric validated for higher education (Gutiérrez Rosado et al., 2025), provides performance descriptors and achievement levels that will ensure inter-evaluative consistency and clarity for students. Its use organizes the observation of key skills, from the specification of the objective to responsible iteration, and promotes comparability between cohorts, causing the evaluation to shift its focus from isolated results to capturing the quality of the inquiry process.

A professionally oriented ecosystem must anchor assessment to disciplinary practices. In cost structure courses, this involves assessing activity identification, driver selection, and indirect cost allocation, in line with ABC approaches that provide more rational information for decision-making. On the other hand, the design of AI-guided tasks should require students to make assumptions explicit, validate data, and compare scenarios, so that automation complements, rather than replaces, accounting judgment (Da Costa Marques, 2012).

Likewise, the empirical literature on ABC in operational contexts shows that accuracy in activity modeling affects cost reduction and strategic planning. Therefore, IAG assessment may ask students to construct activity maps, estimate resource consumption, and compare actual distributions with optimal ranges, recording their verification of each assumption in prompts and reflection notes. This articulation allows for judging not only the correctness of the model, but also the quality of AI-supported decision-making (Zúñiga Marín & Aguirre González, 2022).

Rigor also demands clear and socialized operational ethics. Some classroom experiences with ChatGPT show benefits in discursive cohesion and argumentative structure, but also warn of risks of dependency, diffuse authorship, and plagiarism if its use is not guided correctly. Baldrich & Domínguez-Oller (2024) argue that assessment should include criteria for integrity, citation, and intellectual originality, as well as spaces for meta-reflection on the tool's limits and scope. Therefore, making these criteria explicit in the guidelines and rubrics would avoid misunderstandings, strengthening student autonomy and responsibility.

The ecosystem's scalability is supported by architectures that integrate assistants aligned with the curriculum and verified sources, capable of providing clues, examples, and contextual references. When the assistant documents its responses with citations and excerpts from course materials, the teacher gains traceability, and the student receives relevant, auditable support. This facilitates replication across subjects and cohorts and maintains a standard of pedagogical quality even with large groups. Alier-Forment et al. (2025).

At the same time, comparative evidence on IAG in education suggests advantages in the design of experiences and large-scale support, provided that disciplinary relevance and pertinence are taken into account. In addition, the findings indicate that AI literacy modulates the benefit: those who master contextual and collaborative prompts obtain better results than those who use generic prompts. Therefore, the ecosystem must also evaluate the ability to adapt prompts, combine sources, and review biases as part of learning outcomes (Romani Pillpe et al., 2025).

From a course management perspective, it is advisable to establish formative assessment cycles that combine micro-deliveries with feedback from AI and the teacher. In this sense, algorithmic clues become inputs for human review, not substitutes. In addition, student perceptions of benefits and ethical dilemmas should be monitored with brief instruments, as they influence the acceptance of strategies and their effectiveness. This pedagogical monitoring, with usage data and qualitative evidence, enables transparent adjustments to criteria and workloads (García Sánchez, 2023).

To consolidate validity and reliability, it is recommended to align performance rubrics with learning outcome matrices and cost domain descriptors. For example, the assessment of an ABC prototype with IAG could consider the relevance of activities, the consistency of drivers, the justification of assumptions, and the quality of sensitivity analysis. Complementarily, the prompts rubric would judge the clarity of the objective, the use of context, and iteration decisions. As can be seen, both dimensions converge on triangulated, replicable evidence across semesters. Casanova Villalba et al. (2021).

On the other hand, the reliability of the assessment requires caution when it comes to technological solutions that promise to detect generated texts automatically. Research shows that such detectors are not accurate enough for high-impact decisions, so their use should be avoided as conclusive evidence. In this context, evaluating reasoning, decisions, and work traces is methodologically more robust and reduces false positives that would unfairly affect student performance. Therefore, assessment policy should make this criterion explicit and offer alternative means of verification (García Peñalvo et al., 2024).

Scalability is also achieved through prompt libraries aligned with the curriculum and prompt engineering guidelines, enabling different teachers to apply a common standard. These libraries should be structured by cost scenarios, activities, and constraints, facilitating transfer between subjects and consistency in the student learning experience. In addition, prompting training itself must be grounded in the principles of clarity, context, and guided iteration, as described by Segarra Ciprés et al. (2024) in the university setting.

A decisive component of scalability is personalized tutoring supported by IAG, which can offer differentiated scaffolding without overwhelming the teacher. At this point, if the assistant incorporates validated knowledge bases and generates traceable feedback, teaching benefits from constant and consistent support, and the student progresses with greater autonomy (Borja Borja, 2025). For these reasons, assessment must recognize not only these personalized itineraries, but also their impact on the achievement of competencies, sequentially documenting evidence of both the process and the product.

Methodological rigor requires protocols for continuous review and improvement of the ecosystem. García Peñalvo et al. (2024) argue that, in addition to analyzing achievement rates and product quality, it is advisable to audit algorithmic biases, the relevance of sources, and the adequacy of cost drivers, and to incorporate progressive adjustments. It is suggested that the combination of rapid literature reviews, case studies, and experience evaluation offers an effective route to sustaining quality and relevance, even in scenarios of rapid change driven by the evolution of generative AI.

For the ecosystem to be rigorous, assessable, and scalable, it must articulate three pillars: competencies in prompt engineering with explicit, validated criteria; disciplinary tasks that require accounting judgment in cost structures; and assistance architectures with traceability and operational ethics. On the other hand, prudence in the use of detection tools and the centrality of disciplinary reasoning will be the pillars that sustain academic equity. Therefore, when assessment considers both performance and process, and when AI devices are embedded in robust pedagogical frameworks, scalability ceases to be an abstract promise and becomes a verifiable, sustainable practice (Romani Pillpe et al., 2025).

## FINAL REFLECTIONS

The incorporation of generative artificial intelligence into the teaching of cost structures has proven to be an opportunity to strengthen accounting reasoning, provided it is governed by criteria of quality, ethics, and traceability. In this sense, the technological resource does not replace the student's professional judgment or the teacher's mediation, but rather amplifies the ability to explore scenarios, contrast assumptions, and communicate decisions in a reasoned manner. Recent evidence suggests that this integration requires a review of assessment practices and an update of curricular frameworks to ensure learning is relevant and equitable.

This chapter has argued that didactic rigor is expressed in the clarity of objectives, the quality of data, and the verifiable reconstruction of the calculation process. Therefore, it has insisted on documenting prompts, outputs, and decisions, and on requiring causal explanations for the choice of drivers and allocation bases. This logic is consistent with the nature of ABC and TDABC methods, where the passage from resources to activities and from activities to cost objects requires auditable traces and internal consistency.

Comparative experience suggests that a learning ecosystem with algorithmic tutoring can promote autonomy, self-regulation, and meaningful learning if the scaffolding avoids directive responses and encourages reflection. Therefore, it is advisable to prioritize assistants who ask questions, re-ask questions, and offer alternatives, rather than dictating closed solutions. This perspective shifts the focus from simple procedural correction to conceptual understanding and transfer to real cost management contexts.

It is important that prompt engineering be understood as a cross-cutting and assessable skill, as it mediates the quality of interaction and the depth of reasoning. A student who states purpose, context, data, and success criteria, and who iterates with verification, learns to think with explicit language and controlled evidence. Such metacognitive learning not only reduces the risk of technological dependence but also increases the intelligibility of the process for peer co-evaluation and teacher feedback.

Practices with generative AI are not free of tensions. Doubts persist about accuracy, bias, and authorship responsibility, as well as heterogeneous perceptions among teachers and students regarding usefulness, fairness, and workload. In this vein, it is advisable to combine initial guidance, guided examples, and clear teaching contracts that define permitted uses, mandatory verification, and minimum traceability. Institutional transparency and accountability will therefore be responsible for strengthening trust and informed acceptance of the strategies.

The writing and communication dimension is another area for improvement. When AI support is combined with peer review processes and explicit criteria for responsible authorship, progress can be seen in argumentative coherence and evidence quality, without diluting the requirement for critical thinking. This is particularly relevant in cost reports, where the narrative must explain decisions, risks, and sensitivity, rather than simply presenting spreadsheets.

From a disciplinary perspective, the prototypes presented demonstrate that the link between activity modeling, cost allocation, and sensitivity analysis gains new power when verifiable algorithmic tutoring is integrated. However, the pedagogical value only materializes when practice requires justifying causality, reconciling totals, and defending assumptions against alternative scenarios. In logistics contexts, for example, this requirement allows for the identification of inefficiencies and the reconfiguration of processes with greater precision and timeliness.

The evaluation of the ecosystem must balance product and process. Here, the accuracy of the calculation is important, but even more important is the quality of the reasoning behind it and the consistency of the trajectory of interaction with AI. The methodological option of integrating communicative evaluability and prompt rubrics is appropriate for auditing decisions, detecting biases, and promoting iterative improvements in interaction. This strategy also greatly facilitates replication across cohorts and the consolidation of task libraries and templates with shared standards.

Generative AI is not a shortcut to learning cost accounting, but a means of making reasoning more explicit, the process more transparent, and evaluation more rigorous. The central question is no longer whether the tool is accurate, but rather how its use is governed to enhance learning and the quality of accounting decisions. The evidence indicates that benefits are realized when there are clear frameworks, critical literacy, and systematic verification, conditions that this chapter has translated into concrete instructional design proposals.

The field of study remains open to new research agendas examining differential effects by entry profiles, traces of interaction that predict learning, and impact metrics that harmoniously integrate rigorous criteria of technical, ethical, and communicative quality. Similarly, it is pertinent to examine how prompting and modeling skills evolve throughout the curriculum, and to investigate which combinations of human and algorithmic tutoring would maximize understanding of cost structures in complex contexts such as those of today. This provides the scientific community with a foundation for moving forward with caution and ambition, avoiding false dilemmas, and, above all, prioritizing meaningful learning to achieve truly high-quality education.

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# Chapter 05 / Capítulo 05

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# Classroom experiences with generative AI

## Experiencias de aula con IA generativa

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**ABSTRACT**

The use of generative Artificial Intelligence (AI) has taken special relevance within educational centers and among students of any academic level, this has allowed the deepening of topics and content in a broader way. The main objective of the study was to analyze the classroom experiences with generative AI between n=100 students and n=60 teachers at university level in undergraduate and graduate, using a quantitative, non-experimental approach with a transversal, correlational and descriptive design, which showed that the most used AI is ChatGPT in 48 % and 46,7 %, Gemini 20 % and 25 %, Copilot 17 % and 20 %, also, a strong positive correlation was evidenced between classroom experiences with generative AI by the student of r=0,875** with a shared variance $r^2$=76,60 % and for the teacher r=0,851** with $r^2$=72,50 % with the pedagogical use that is currently given, concluding that digital tools favor in some way educational practices, however, it is necessary to consider the ethical and developmental implications that these may derive among the main users in educational environments.

**Keywords:** Generative AI; Ethics; Virtual Environments; Didactic Planning; Scientific Research; Pedagogical Use; Technologies; Learning.

**RESUMEN**

El uso de la Inteligencia Artificial (IA) generativa ha tomado especial relevancia dentro de los centros educativos y entre los alumnos de cualquier nivel académico, ello ha permitido la profundización en temas y contenidos de una manera más amplia. El objetivo principal del estudio fue analizar las experiencias del aula con IA generativa entre n=100 alumnos y n=60 docentes a nivel universitario en pregrado y posgrado, mediante un enfoque cuantitativo, no experimental con un diseño transversal, correlacional y descriptivo, el cual permitió evidenciar que la IA más utilizada es ChatGPT en un 48 % y 46,7 %, Gemini 20 % y 25 %, Copilot 17 % y 20 %, también, se evidenció una correlación positiva fuerte entre las experiencias de aula con IA Generativa por el alumno de r=0,875** con una varianza compartida $r^2$=76,60 % y para el docente r=0,851** con $r^2$=72,50 % con el uso pedagógico que se le da actualmente, concluyendo que las herramientas digitales favorecen en cierto modo las prácticas educativas, sin embargo, es necesario considerar las implicaciones éticas y de desarrollo que estas puedan derivar entre los usuarios principales en los entornos educativos.

**Palabras clave:** IA Generativa; Ética; Entornos Virtuales; Planificación Didáctica; Investigación Científica; Uso Pedagógico; Tecnologías; Aprendizaje.

## INTRODUCTION

Artificial intelligence (AI) is an increasingly important tool in classrooms in all areas of education, whether private or public, at the elementary, middle, and high school levels. Its incorporation allows new technologies to be integrated into pedagogical and teaching spaces, further enriching the educational culture among the student community. This facilitates the growth of new generations adapted to emerging changes in the face of the disruptions demanded by society, with broad tolerance for globalization and international competition.

This transformation brings both advantages and challenges, as it offers ample opportunities to personalize teaching and learning styles, with a view to optimizing educational management by applying forms of knowledge assessment across the various areas of knowledge. However, challenges arise in every environment in which it is used, which can compromise professional ethics with its uses and applications, technical implications for its management and mastery; also, at the pedagogical level, teachers must be prepared to understand its administration and master the teaching techniques aimed at its use in the classroom (Peñafiel Arteaga et al., 2025).

The new generations bring with them a thirst for knowledge, work, and mastery of new tools, as they are born, grow, and develop in an increasingly technological and changing environment driven by new global trends demanded by labor and education markets. Given this scenario, teaching professionals must prepare for these demands by continually training to support the educational programs developed in academia, aiming to create, educate, and transform teaching into a pillar of intellectual enrichment.

The technological evolution that has emerged and reached different educational institutions at the click of a button via computers, smartphones, and other electronic devices used in everyday life has made it possible to rethink the role of education and educational centers in light of the existing need to develop cognitive abilities in line with the advancement of technologies and machines that are doing so at an unprecedented speed. The opportunities to develop educational skills and to develop them towards the growth of human abilities, which at this point are irreplaceable by a machine as such, require the creation of a synergy between what AI can do and what humans can manage (Sevilla et al., 2025).

Faced with the increase, evolution, and paradigm shift from traditional education to one better adapted to technology, the challenges are becoming increasingly complex because many people of low socioeconomic status do not have access to these devices, the internet, and other tools essential to developing classroom content. Added to this is conformism and a lack of training. A report by the Microsoft Education Team (2025) compiled a series of statistics that should be considered relevant to this study:

1. 86 % of educational organizations currently use generative AI, and its use has increased among both students and educators.
2. Forty-five percent of educators worldwide and 52 % of U.S. students say they have not received any training.
3. Students are concerned about being accused of plagiarism (33 %) and dependence on AI (30 %).
4. The primary concern among educators is plagiarism (31 %), followed by excessive dependence (21 %), misinformation (20 %), security (20 %), and insufficient training (20 %).
5. Leaders are concerned about ethical weaknesses (21 %), lack of technological preparedness (20 %), and equitable access (18 %).
6. 47 % of business leaders believe their employees' AI literacy needs improvement,

and 66 % would not hire someone without this knowledge and mastery.

This vast ecosystem of changes, opportunities for improvement, needs, and intellectual enrichment within the educational and work spheres is becoming increasingly evident, significant, and necessary for educators, students, and academic institutions. However, any limitations that may be present must be addressed to turn them into strengths in the training of future professionals, so that they can develop the skills demanded by an increasingly competitive and demanding world of work.

The acceleration of AI applications in education is facilitating increasingly efficient, diverse, and personalized learning environments tailored to the academic area being addressed, enabling the identification of learning patterns and individualized recommendations for performance. However, challenges such as heavy reliance on this tool, its unethical use for plagiarism, and the failure to develop critical thinking because students ask the tool to do it for them, among others, create difficulties in its use and application (Puche-Villalobos, 2024).

Consequently, AI is a powerful tool that can serve as a strategic ally for educational institutions, teachers, and students. When used well, it amplifies their ideas, simplifies their work, and unlocks new teaching and learning opportunities, accelerating their education. It should also be noted that AI has not come to replace traditional learning methods, but rather to boost creativity and support training through experience towards the development of increasingly competent professionals in the responsible use of AI, as required by business leaders. Hence, there is a need to analyze classroom experiences with generative AI.

Faced with this new digital scenario, driven by the Covid-19 pandemic, virtual classrooms became the focus of attention in different educational institutions, generating a lot of uncertainty for those who had never participated in these environments. as well as using new tools or devices that changed their view of education, not only for learners, but also for teachers who had to coordinate their content and activities in such a way as to avoid stress, connectivity difficulties, adaptation to digitization, and distractions that were not previously present in a face-to-face classroom. This leads to verifying the importance of a virtual classroom in the teaching and learning process.

It is essential to understand that the emergence of generative artificial intelligence in education has transformed teaching and learning, creating more dynamic training models that can be customized to the needs of each professional, academic area, and job market. Tools such as ChatGPT, Copilot, and Gemini have transformed the way teachers and students perform tasks, including writing, summarizing, problem-solving, and generating academic content. Studies show that AI is critical in 52,6 % of cases because it optimizes time spent searching for educational information; in 41,4 % of cases, it is almost always important; and in 6 % of cases, it is not relevant (Menacho Ángeles et al., 2024).

It is essential to recognize that the Technology Acceptance Model (TAM) developed by David (1989) applies to this study, as perceived usefulness and ease of use of new technologies determine the capacity for adaptation, adoption, and technological application. Precisely in the context of generative artificial intelligence, all of this allows students to understand that it will improve their academic performance and, therefore, their professional development. This underscores the need to understand students' perceptions of the use of generative AI in the classroom for their learning.

Based on the above, the use of generative AI will allow users to interact extensively with various forms of knowledge representation within the library, each tool offering them greater active engagement, thus promoting autonomy and creativity among students.

In this sense, it is accepted as a tool that facilitates the personalization of learning inside and outside the classroom, as it generates an automated feedback process and a high reproduction of new, innovative, and easily replicable educational content, thus transforming the conservative academic role of the teacher into that of a facilitator and mediator (García-Peñalvo et al., 2024). Therefore, it is feasible to determine the level of pedagogical use of generative AI by students.

It is essential to mention that the impact of generative AI on knowledge acquisition is directly related to the theory of meaningful learning developed by David Ausubel in 1968, who highlighted the need to be able to make a direct connection between new content and previously acquired knowledge, which can be directly linked thanks to the ease with which this tool offers personalized contributions through examples of current and comparative contexts that can be drawn from past events. This will enable students to develop competent critical thinking skills (Pinzón Arteaga, 2024).

Therefore, it is necessary to specify the impact that AI has when implemented in the classroom, because it contributes significantly to student learning, as its use in academic content and subject development can act as a cognitive mediator to facilitate meaningful learning between users and the teacher who has prepared the academic load based on the thematic structure of the subject being taught.

However, within the line of ethical and responsible thinking about the use of AI in educational environments, different positions have been generated, including the following:

1. Paguay Simbaña et al. (2024) stated that "the design and development of AI technologies must respect the ethical foundations of educational work," which aligns with this study's focus on the ethical and favorable use of these tools in teaching. However, special attention must be paid to the concerns about the application of these methods, ensuring that the private information of users and institutions is protected.
2. Molina Mera et al. (2025) stated that "in this context, fundamental ethical and social concerns arise, such as: bias and discrimination, privacy and security, technological dependence, resistance to change, and lack of training." This opinion contributes to this study, which focuses on the limitations and challenges that AI use can raise in the educational context, not only for students but also for faculty, who must be highly trained and focused on these methodologies.
3. Arteaga-Zambrano et al. (2025) identified that "in the educational field, these tools can help optimize, individualize, and make teaching and learning processes more effective; however, it was noted that it is essential that the use of this technology be carried out under standards of ethics and responsibility." In terms of the contribution to this study, it is necessary to recognize that while it is true that AI is a support, tool, or technological advisor for the educational system, it is essential to understand the role it plays in teaching and the limits that must be established with students and the extent to which it can interfere in their activities. Its role is to facilitate, not to substitute for or limit their abilities, critical thinking, and cognitive development.
4. Estrada Tigsilema (2024) highlighted "the importance of transparency and accountability in the development and use of educational algorithms, the need to address biases and ensure equity and accessibility for all students." The fundamental contribution

of this study is concerned with the appropriate use of AI: that it be equally accessible to the entire student body regardless of social position, and that it be supervised to avoid bias and ensure correct application.

These contributions demonstrate that the ethical use of generative AI in the classroom is vital. The authors warn that clear guidelines and training are needed to raise awareness of responsible use, as there are no restrictions on content use, which facilitates plagiarism, inequality, and algorithmic bias. In this regard, ethical literacy in AI is essential to promote consistent use in the academic activities of educational institutions.

Based on the above, there is a need to identify that the greater the pedagogical use of generative AI, the greater the ethical and responsible awareness among students.

The arrival and implementation of AI in the education system can present both opportunities and challenges, not only for students, but also for teachers and educational centers, because it suggests a process of change, adaptation, and monitoring of how these elements can be articulated in academic activities so that the results they contribute are valuable for overall educational performance.

Below are differences derived from the postulates of other authors, highlighting the benefits and challenges that can be addressed with AI and the ones that arise in the results.

**Table 5.1** Challenges and opportunities of AI according to authors

| # | Opportunities | Challenges | Authors and year | Country |
|---|---|---|---|---|
| 1 | Personalization of learning, Automation of tasks. | Ethics and responsibility | Gracia Loor, (2025) | Ecuador |
| 2 | Inclusion, sustainability, and future prospects, automation of academic tasks, and real-time content generation. | Pedagogical dynamics and teacher adaptation, assessment, ethics, and educational quality. | Acevedo Carrillo et al., (2025) | Peru |
| 3 | Automating administrative tasks, personalizing learning and improving digital competence, collaborative learning, and developing skills. | Misuse of generative tools, lack of clear guidelines and training | Gonzalez Said de la Oliva, (2025) | Peru |
| 4 | Improved content and access to information, efficiency and time optimization, creativity and productivity, administrative facilitation, educational support and complementarity, inclusivity, and diversity of viewpoints | Technical problems, ethical concerns, lack of training, resistance to change | Kroff et al., (2024) | Chile |
| 5 | Universal access, machine learning, language modeling and semantic analysis, intelligent content, content analysis, automation of management and administrative tasks | Teacher training, detection of plagiarism and AI-generated texts, ethical treatment and confidentiality of data, resource optimization | Boujenna et al., (2024) | Spain |
| 6 | Generating materials, stimulating creativity, performing systematic processes efficiently, and facilitating academic life | Ethical implications of its use, restrictions on the use of these resources, limitations on the performance of specific tasks, reduction in learning capacity. | Chao-Rebolledo and Rivera-Navarro, (2024) | Mexico |

It is essential to consider that implementing processes that automate educational activities enables more personalized learning tailored to the characteristics of each academic grade. These well-managed tools, driven by AI-generated algorithms that generate new knowledge, operate in an agile, rapid manner and invigorate different educational levels. However, to preserve their efficiency, commitment, and results, they must be operated ethically, maintain trained staff and committed students, and ensure information security both inside and outside institutions to reduce any negative actions that may arise.

## DEVELOPMENT

The research used a quantitative methodology, collecting statistical data on ordinal-level variables. In addition, a Likert attitude scale with five response options, ranging from strongly agree to disagree strongly, was used to collect generalizable quantitative data. A non-experimental design was also used because no experiments were conducted, and the variables were not deliberately manipulated; rather, the facts were studied as they occurred in the environment under study.

In this way, correlations and inferences were made among the main elements evaluated (variables and dimensions), which enabled us to identify the data of interest to answer the proposed questions. Similarly, a descriptive design was used to describe the main characteristics through graphical representations and tables for easier understanding. The study population consisted of 100 university students and 60 teachers at the higher education level who use AI in their academic activities.

It is worth noting that this unit of analysis was chosen because it directly corresponded to the topic under study, thereby prompting the use of the snowball sampling technique. The researchers collected data on members of the target population who used these digital tools and then asked participants to provide the information necessary to locate other colleagues who met these characteristics, thus applying the survey progressively (Hernández-Sampieri & Mendoza Torres, 2023).

Two measurement instruments were developed. The questionnaire contained 27 questions across different sections, with five additional questions per section on sociodemographic issues, all aimed at obtaining general data on perceptions of the educational community. The questionnaires were designed and administered in a digital, self-administered format, one for teachers and one for students, and were provided electronically via *Google Forms*.

To ensure the questionnaire's content validity, it was reviewed by three experts in higher education, educational technologies, and scientific research and analysis, who evaluated each item against semantic criteria, relevance, intentionality, and sufficiency. It was also supported by the literature on its development.

To test construct validity, an exploratory factor analysis (EFA) was used to confirm that the elements are correlated and to establish the relevant dimensions based on this grouping. Furthermore, based on the main results obtained through the Kaiser-Meyer-Olkin (KMO) test and Bartlett's sphericity test as statistical measures of EFA, according to Kaiser (1974), the following criteria were used to evaluate the KMO:

- Above 0,91 ⇒ Acceptable
- KMO from 0,81 to 0,90 ⇒ Good
- KMO from 0,71 to 0,80 ⇒ Average
- KMO from 0,61 to 0,70 ⇒ Mediocre

- KMO from 0,51 to 0,60 ⇒ Terrible
- KMO Below 0,50 ⇒ Unacceptable

Regarding Bartlett's sphericity test, it was proposed that:

- A significant Bartlett test ($p < 0,05$) indicates that the variables are significantly correlated and that factor analysis can be performed.
- A non-significant Bartlett test ($p > 0,05$) suggests that the variables are not significantly correlated and that factor analysis may not be appropriate.

**Table 5.2.** KMO and Bartlett's test for the variable classroom experiences with generative AI

| | | |
|---|---|---|
| **KMO and Bartlett test survey for students** | | |
| Kaiser-Meyer-Olkin measure of sampling adequacy | | 0,833 |
| Bartlett's sphericity test | Approx, Chi-square | 1192,814 |
| | Gl | 351 |
| | Mr, | 0,000 |
| **KMO and Bartlett test survey for teachers** | | |
| Kaiser-Meyer-Olkin measure of sampling adequacy | | 0,861 |
| Bartlett's sphericity test | Approx, Chi-square | 1376,987 |
| | Gl | 351 |
| | Sig, | 0,000 |

The KMO indices were 0,833 and 0,861, respectively, and Bartlett's sphericity test was significant ($p < 0,001$), confirming the suitability of the instrument for an exploratory factor analysis.

**Table 5.3.** EFA for the variable classroom experiences with generative AI

| | Rotated component matrix | Component | | | |
|---|---|---|---|---|---|
| **Dimension** | **Indicator** | **1** | **2** | **3** | **4** |
| Pedagogical use of generative AI | Use of AI in academic activities | 0,708 | | | |
| | Use of AI to facilitate students' lives | 0,686 | | | |
| | Use of AI facilitates learning | 0,679 | | | |
| | AI use impacts students | 0,546 | | | |
| | Use of AI as a tool of the future | 0,456 | | | |
| | AI use promoted by teachers | 0,438 | | | |
| | Use of AI in subjects | 0,430 | | | |
| Student perception | Satisfaction with using AI | | 0,816 | | |
| | Using AI promotes ideas and work | | 0,702 | | |
| | Improved performance | | 0,677 | | |
| | AI improves academic results | | 0,650 | | |
| | AI facilitates autonomous learning | | 0,626 | | |
| | AI stimulates creativity | | 0,558 | | |
| | AI is easy and accessible to use | | 0,535 | | |
| Impact on learning | Improves critical thinking | | | 0,822 | |
| | Facilitates collaborative learning | | | 0,820 | |
| | Support with complex topics | | | 0,736 | |
| | Improves understanding of content | | | 0,708 | |
| | Improves in-depth analysis | | | 0,665 | |
| | Development of digital skills | | | 0,472 | |

| | | |
|---|---|---|
| Ethics and responsibility | Decreased learning ability | 0,765 |
| | Risks of plagiarism | 0,719 |
| | Restriction of use. | 0,710 |
| | Ethical implications of its use | 0,685 |
| | Penalty for lack of academic authorship | 0,613 |
| | Responsible use of AI | 0,607 |
| | Little distinction between use and plagiarism | 0,497 |

Extraction method: principal component analysis
Rotation method: Varimax with Kaiser normalization.
a. The rotation converged in 9 iterations.

An exploratory factor analysis (EFA) was performed. The results showed consistent groupings between items and dimensions, with factor loadings greater than 0,430 in most of them. In addition, the principal component extraction method with varimax rotation was used.

Internal reliability was assessed using Cronbach's alpha statistic, which yielded the following result:

**Table 5.4.** Internal consistency Cronbach's alpha

| **Dimension** | **Cronbach's alpha** | |
|---|---|---|
| | **Instrument for students** | **Instrument for teachers** |
| Pedagogical use | 0,859 | 0,881 |
| Student perception | 0,912 | 0,776 |
| Impact on learning | 0,885 | 0,802 |
| Ethics and responsibility | 0,779 | 0,775 |
| Total, instrument | 0,920 | 0,879 |

**Table 5.5.** Information for interpretation correlation coefficient

| **Scale** | | **Type of correlation** |
|---|---|---|
| -1,00 | | = Perfect negative correlation. |
| -0,90 | -0,99 | = Very strong negative correlation. |
| -0,75 | -0,89 | = Considerable negative correlation. |
| -0,50 | -0,74 | = Average or moderate negative correlation. |
| -0,25 | -0,49 | = Very weak negative correlation. |
| -0,10 | -0,24 | = Negligible negative correlation. |
| 0,00 | -0,09 | = There is no correlation between the variables. |
| 0,00 | +0,09 | = There is no correlation between the variables. |
| +0,10 | +0,24 | = Insignificant positive correlation. |
| +0,25 | +0,39 | = Very weak positive correlation. |
| +0,40 | +0,49 | = Weak positive correlation. |
| +0,50 | +0,59 | = Medium or moderate positive correlation. |
| +0,60 | +0,74 | = Acceptable positive correlation. |
| +0,75 | +0,79 | = Considerable positive correlation. |
| +0,80 | +0,89 | = Strong positive correlation. |
| +0,90 | +0,99 | = Very strong positive correlation. |
| +1,00 | | = Perfect positive correlation. |

Source: prepared by Aaron Umanzor, adapted from the authors (Hernandez-Sampieri & Mendoza Torres, 2023) .

Based on the results obtained, it was determined that the instrument, has an acceptable level of reliability and is free of bias. To interpret the correlational analysis using Pearson's statistic (table 5.5).

The interpretation of bilateral significance will be based on:

1. Significant at the 0,05 level with 95 % certainty that the correlation is accurate and a 5 % margin of error.
2. Significant at the 0,01 level with a 99 % probability that the correlation is accurate and a 1 % margin.

It should be noted that using this entire statistical process ensured the data were robust and reliable, confirming their acceptability. Furthermore, there were no limitations before, during, or after the research, so logical conclusions were reached and supported by empirical data that can be replicated using a widely accepted scientific method.

## RESULTS

Regarding student participation, 60 % were female, which is a reasonably high proportion. This allows us to determine that their inclusion in academic training is highly participatory, leaving behind the paradigms of patriarchy. In contrast, 40 % were male, suggesting that some topics are less interesting or less relevant in this era of change and adaptation to new technological trends.

Student interest is also evident, with high participation rates among undergraduate students (35 %) and master's students (65 %). Furthermore, these data highlight the relevance of how new technologies can benefit academic processes by gender and level of study. In terms of faculty participation, it was found that women predominate, with 51,7 % teaching at the higher education level, demonstrating that women have increasingly taken control of processes that were more complex in the past and are now more widely considered (table 5.6).

**Table 5.6.** Cross-tabulation table: Gender and academic level studied

| Gender | Academic level studied | | | | Total | |
|---|---|---|---|---|---|---|
| | Undergraduate | | Master's | | | |
| | No. | % | No. | % | No. | % |
| Female | 17 | 48,6 | 43 | 66,2 | 60 | 60 |
| Male | 18 | 51,4 | 22 | 33,8 | 40 | 40 |
| Total | 35 | 100 | 65 | 100 | 100 | 100 |

Men account for 48,3 % of participation, demonstrating that gender diversity in education is strong and inclusive, suggesting that opportunities have opened up in almost equal measure for both genders (table 5.7).

It was determined that the use of AI is conditioned by certain moments or needs, and also that students and teachers do not use the same type (table 5.8). Of these, the most used is ChatGPT 48 % with a usage factor of 18 % weekly and 14 % monthly, Gemini with 20 % is the second most used with 8 % weekly, the others (daily, monthly, and rarely) 4 % each, in third place, Copilot with 17 % and 6 % monthly usage, 5 % daily, and other AIs at 15 % with weekly usage of 8 %.

**Table 5.7.** Cross-tabulation table Gender and academic level of teaching staff

| Gender | Academic level of teaching | | | | Total | |
|---|---|---|---|---|---|---|
| | Undergraduate | | Master's | | | |
| | No. | % | No. | % | No. | % |
| Female | 21 | 50 | 10 | 55,6 | 31 | 51,7 |
| Male | 21 | 50 | 8 | 44,4 | 29 | 48,3 % |
| Total | 42 | 100 | 18 | 100 | 60 | 100 |

**Table 5.8.** Type of AI used by students and teachers

| Type of AI | Students | | Teachers | |
|---|---|---|---|---|
| | No. | % | No. | % |
| ChatGPT | 48 | 48 | 28 | 46,7 |
| Gemini | 20 | 20 | 15 | 25 |
| Copilot | 17 | 17 | 12 | 20 |
| Other | 15 | 15 | 5 | 8,3 |
| Total | 100 | 100 | 60 | 100 |

On the other hand, the AI most used by teachers is ChatGPT, with 46,7 % using it weekly, 9 % monthly, and 7 % almost never. In addition, Gemini is used by 25 % weekly, Copilot by 20 % weekly, and others by 8,3 % with a frequency of use of 2 % almost never, This shows that for both participants, the use of AI has become relevant according to the needs that drive them to consider its application in their academic activities, thus stipulating that although some are not used sequentially, they are used when a need arises, which is in agreement with (Menacho Ángeles et al., 2024) .

Based on this, to analyze classroom experiences with generative AI, the participation of both genders has been considered relevant for both teachers and students. However, it is necessary to know how they use the tool:

**Table 5.9.** Uses of AI by students and teachers

| Type of use according to students | No. | % | Type of use according to teachers | No. | % |
|---|---|---|---|---|---|
| Search for general information | 21 | 21 | General inquiries | 14 | 23,3 |
| General inquiries | 19 | 19 | Generating ideas for teaching classes | 11 | 18,3 |
| Support for understanding class content | 16 | 16 | Show examples of its use in class | 8 | 13,3 |
| Generation of ideas and inspiration | 16 | 16 | Designing teaching materials | 8 | 13,3 |
| Search for scientific research | 13 | 13 | Scientific research | 8 | 13,3 |
| To carry out their tasks or assignments | 12 | 12 | Support for lesson planning | 7 | 11,7 |
| To avoid doing schoolwork on their own | 3 | 3 | To evaluate work | 4 | 6,7 |
| Total participation | 100 | 100 | Total, participation | 60 | 100 |

Students showed a predominance of information search (21 %) and general queries (19 %), indicating that they require tools to facilitate the acquisition of specific knowledge. In addition, content comprehension (16 %) and idea generation (16 %) were prominent, suggesting that creativity can be boosted with this tool. 13 % of searches are for scientific documents, demonstrating the growing relevance of research in this field. On the other hand, 12 % use it to complete their assignments, and 3 % to avoid doing tasks themselves, so it is a support tool for combining their activities and the help they require.

As for teachers, general consultations (23,3 %), idea generation (18,3 %), and classroom examples have been the most prevalent. In this regard, it is appreciated that AI contributes to creativity and support for improving these teaching materials (13,3 %) by using innovative ideas and quality information, reliability for their subjects, and also carrying out scientific research (13,3 %), promoting the generation of new knowledge in academia and the scientific community, relying on this for teaching planning (11,7 %) on how to integrate all these processes into their syllabus, and some carry out the evaluation of work (6,7 %), which shows that they still prefer to do it directly and not let a tool do it for them, except for this percentage, which is still low in relation to the other results. This confirms a broad adaptation to new trends, in line with (Palmera Quintero et al., 2025).

All of this made it possible to verify the level of importance of a virtual classroom in the teaching and learning process for students and teachers, within which it has been understood that this new adaptation allows for synergy between the use of electronic devices with applications that improve educational quality and facilitate the acquisition of new knowledge.

**Table 5.10.** Experiences with generative AI and its pedagogical use at the student and teacher level

| **Correlations** | | **Pedagogical use of generative AI by students** | **Pedagogical use of generative AI by teachers** |
|---|---|---|---|
| Classroom experiences with generative AI (GAI) | Pearson correlation | 0,875** | 0,851** |
| | Sig. (two-tailed) | 0,000 | 0,000 |
| | N | 100 | 60 |
| | r squared | 0,766 | 0,725 |
| | Anova regression Sig. | 0,000 | 0,000 |

**. The correlation is significant at the 0,01 level (bilateral).

The results showed a strong positive correlation between the experiences of both the student 0,875** and the teacher 0,851 ** in the classroom with the use of generative AI, which has allowed for significant and high pedagogical use, in accordance with the results obtained with a P-value < alpha value 0,01, demonstrating that they are statistically significant with a shared variance $r^2$=76,6 % for students and $r^2$=72,5 % for teachers, which reinforces the link between the use of digital tools and the experiences that can occur within a classroom.

Regarding the regression model used, the ANOVA results showed that the effect is statistically significant, confirming that the variable classroom experiences with AI-G has a tangible impact on the variable pedagogical use. As classroom experiences with generative AI increase, so does its pedagogical use by students. This confirms that a virtual classroom in the teaching and learning process has taken on special importance for both students and teachers, so their experiences with AI-G have been extensive, in line with (Puche-Villalobos, 2024).

To understand students' perceptions of the use of generative AI in the classroom for learning, it was necessary to identify the elements directly related to it, given that its pedagogical use yielded favorable results. However, some elements were more significant than others.

The results showed an acceptable positive correlation with the use of Generative AI in academic activities (0,709** with $r^2$=50,3 %), in facilitating students' lives (0,623** with $r^2$=38,8 %), facilitating learning (0,731** with $r^2$=53,4 %), and use in subjects (0,683** with $r^2$=46,7 %).

| **Table 5.11.** Perception of the use of generative AI in student learning | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Correlations between the use of AI-G** | | | | | | | |
| Pedagogical use of generative AI | **Academic activities** | **Makes students' lives easier** | **Facilitates learning** | **Student impact** | **Tool of the future** | **Promoted by teachers** | **Use in subjects** |
| Pearson correlation | 0,709** | 0,623** | 0,731** | 0,777** | 0,855** | 0,869** | 0,683** |
| Sig. (bilateral) | 0,000 | 0,000 | 0,000 | 0,000 | 0,000 | 0 | 0 |
| N | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| R squared | 0,503 | 0,388 | 0,534 | 0,604 | 0,731 | 0,755 | 0,467 |
| Anova regression Sig. | 0,000 | 0,000 | 0,000 | 0,000 | 0,000 | 0 | 0 |
| **. The correlation is significant at the 0,01 level (two-tailed). | | | | | | | |

This demonstrated a significant perception of how all these processes can be integrated into academic activities without compromising results, provided that they are regulated and well managed by educational institutions and teachers.

There was also a considerable positive correlation with the impact these tools can have on students (0,777**), with an $r^2$=60,4 %, which provides a clear picture of how these tools are viewed by students in academic training. In addition, there is a strong positive correlation with the future (0,855** with $r^2$=73,1 %) and with these being promoted by teachers (0,869** with $r^2$=75,5 %). In this sense, it can be seen that AI will continue to evolve, making it necessary for teachers to apply and manage it appropriately in educational environments, as evidenced by their relationships and the high levels of shared variance.

Regarding the regression model used, the result of the ANOVA showed that it is statistically significant, thus confirming that the variable pedagogical use of generative AI has a real effect on the variables use of AI in academic activities, use of AI as a s that facilitates students' lives, use of AI that encourages learning, use of AI that impacts students, use of AI as a tool of the future, use of AI promoted by teachers, and use of AI in subjects. As the pedagogical use of the tool increases, it favors all these processes related to student learning. This acceptance is consistent with the theory of technology acceptance (TAM) (Davis, 1989).

Based on this, it was possible to determine the level of pedagogical use of generative AI by students, demonstrating that the tools offer opportunities across different areas and that these are the ones that favor their learning, which was highly significant at the 0,01 level. Based on this data, the impact of AI on classroom learning, especially on students, was specified.

| **Table 5.12.** Impact of AI on learning in a classroom | | |
|---|---|---|
| **Correlations** | | **Student perception** |
| Impact of AI on learning in the classroom | Pearson correlation | 0,716** |
| | Sig, (two-tailed) | 0,000 |
| | N | 100 |
| | r squared | 0,513 |
| | Anova regression Sig, | 0,000 |
| **. The correlation is significant at the 0,01 level (bilateral). | | |

The results showed that AI benefits learning according to students' perceptions, with an acceptable positive correlation of 0,716** and a shared variance of $r^2$=51,3 %. In addition, the regression model used in the ANOVA showed that the result is statistically significant, confirming that these variables are highly related, as indicated by the P-value (99 % probability that the correlation is accurate and a 1 % margin of error). Therefore, the more AI is used in the classroom, the greater its impact on students, consistent with Pinzón Arteaga (2024).

Undoubtedly, these tools make students' lives easier in many ways; however, they create a lot of work for teachers, who must constantly update and monitor the technical aspects, criteria for use and implementation of the tools, as well as the ethics with which they are used to avoid plagiarism and recognition problems. This makes it imperative to clarify the ethical role AI plays in all this work. It was found that the greater the pedagogical use of generative AI, the greater the students' moral and responsible awareness.

The results (table 5.13) showed that there is a very weak positive relationship (0,257**) between the variable "educational use of generative AI" and ethics and responsibility in students, as well as a shared variance of $r^2$=6,60 %, which indicates a low explanatory capacity of the model and that work needs to be done on the ethical development of students with AI. Although the relationship is statistically significant at the 0,01 level (P-value), the strength of the link is limited. Despite this, the ANOVA shows that the regression model is statistically significant; however, the low $r^2$ value limits its predictive usefulness, as noted above.

**Table 5.13.** Educational use of generative AI, greater ethical and responsible awareness

| **Correlations** | | **Ethics and responsibility** |
|---|---|---|
| Educational use of generative AI | **Pearson correlation** | 0,257** |
| | Sig. (two-tailed) | 0,010 |
| | N | 100 |
| | r squared | 0,066 |
| | Anova regression Sig. | 0,01 |

**. The correlation is significant at the 0,01 level (bilateral).

These results have made it clear that, although the relationship between these two variables evaluated is statistically significant, its practical impact is limited. The use of AI in education can shape students' ethics and sense of responsibility. Nevertheless, the finding suggests that elements such as teacher support in the use of AI, instructions, and training may play an essential role in ensuring its proper application, consistent with (Paguay Simbaña et al., 2024).

Among the indicators that may influence this result are penalties for lack of academic authorship 0,656** $r^2$=43,03 %, the lack of distinction between use and plagiarism by teachers 0,619** $r^2$=38,32 %, the ethical implications of its use 0,615** $r^2$=37,82 %, decreased learning ability 0,613** $r^2$=37,58 %, restrictions on use 0,577** $r^2$=33,29 %, the risks of plagiarism 0,535** $r^2$=28,62 %, and the responsible use of AI 0,395** $r^2$=15,60 %, which is consistent with (Molina Mera et al., 2025).

The most attractive benefits for students (table 5.14) were identified as improved content through access to information (17 %), simplification of academic life (16 %) due to the amount of studies and other documents they have access to with AI, optimization of time and productivity (16 %) because it favors them in terms of openness of use and management, fostering learning development (15 %), content analysis (14 %), automating the search for information for their tasks (11 %), and 11 % believe that it allows them to develop their collaborative learning and skills. Therefore, AI for students is an effective and important tool.

Teachers favor (table 5.14) it for personalizing learning according to the type of student (16,7 %), helping them optimize time, creativity, and productivity (16,6 %), facilitating better planning of their activities, developing collaborative learning with better skills (15 %), and supporting them with the generation of intelligent content 15 %, automate academic management and administration tasks 13,3 %, facilitate access to information 11,7 %, and academic life 11,7 %. However, if these benefits are not well managed and developed ethically, they can generate conflicts and difficulties within the classroom, consistent with (García-Peñalvo et al., 2024).

**Table 5.14.** Benefits of using AI

| Benefit for the student | No. | % | Benefits for teachers | No. | % |
|---|---|---|---|---|---|
| Improved content and access to information | 17 | 17 | Personalization of learning | 10 | 16,7 |
| Facilitates academic life | 16 | 16 | Optimization of time, creativity, and productivity | 10 | 16,6 |
| Optimization of time, creativity, and productivity | 16 | 16 | Collaborative learning and skills development | 9 | 15 |
| Promote learning development | 15 | 15 | Generation and analysis of intelligent content | 9 | 15 |
| Generation and analysis of intelligent content | 14 | 14 | Automating academic management and administration tasks | 8 | 13,3 |
| Automate information searches for their tasks | 11 | 11 | Improving content and access to information | 7 | 11,7 |
| Develops collaborative learning and skill development | 11 | 1 1 % | Makes academic life easier | 7 | 11,7 |
| Totals | 10 | 100 | Totals | 60 | 100 |

**Table 5.15.** Challenges of using AI

| Challenge for the student | No. | % | Challenge for teachers | No. | % |
|---|---|---|---|---|---|
| Threat to academic integrity (facilitates plagiarism and unethical use) | 17 | 17 | Ethical implications of its use (responsibility) | 12 | 20 |
| Uneven AI literacy | 13 | 13 | Teaching adaptation | 8 | 13,3 |
| Educational quality | 12 | 12 | Educational quality | 8 | 13,3 |
| Isolation and lack of human interaction | 17 | 17 | Lack of clear guidelines on the use of AI | 7 | 11,7 |
| Lack of AI application in subjects | 11 | 11 | Lack of training | 10 | 16,7 |
| Biased and inaccurate information | 12 | 12 | Resistance to change | 6 | 10 |
| Excessive dependence and reduced critical thinking | 18 | 18 | Decreased learning ability and critical thinking | 9 | 15 |
| Totals | 10 | 100 | Totals | 60 | 100 |

When highlighting the challenges that can be addressed with AI for students (table 5.15), the most critical ones are plagiarism and unethical use (17 %), due to the inappropriate practice of consulting, copying, and pasting. Uneven AI literacy (13 %), as many are unaware of these tools. Educational quality (12 %) is affected because they do not learn equally (11 %), they disconnect from valuable knowledge because they allow the tool to do everything for them, creating excessive dependence and reduced critical thinking (18 %), often isolating its users from reality (17 %), and creating biased and inaccurate content (12 %).

Teachers (table 5.15) should bear in mind the ethical implications of its use (20 %), especially maintaining a straightforward adaptation (13,3 %) to these new electronic and emerging processes to improve educational quality (13,3 %) without being affected by the use of AI, and issuing clear guidelines on its use (11,7 %). To do this, it is necessary to provide training 16,7 %, since a lack of knowledge can generate resistance to change 10 %. The excessive use of these technologies by students can lead to a decrease in learning and critical thinking skills 15,5 %, which is in line with Gracia Loor,(2025); Acevedo Carrillo et al.,(2025); Gonzalez Said de la Oliva,(2025); Kroff et al.,(2024); Boujenna et al., (2024); Chao-Rebolledo and Rivera-Navarro,(2024) and Arteaga-Zambrano et al.,(2025), because the use of this technology must be carried out with standards of ethics and responsibility.

## CONCLUSIONS

The results showed that classroom experiences with generative AI are linked to its pedagogical use by both teachers and students, leading to the understanding that its application is driven by specific requirements in the teaching and learning processes, depending on the subject taught. The use of digital tools has enabled the generation of attractive, current, and trending content in the scientific field for teaching planning. This has led to the understanding that a virtual classroom has proven essential for integrating technologies through flexible processes in academic training. As its implementation progresses, the quality of learning will benefit. Therefore, strategic virtual environments focused on ethics and inclusive of all students must be designed.

Students' perceptions of the use of generative AI in the classroom for learning have been significant. However, although the tools are invaluable for finding relevant and innovative information in each field of study, students become dependent on them for instruction and expect to be provided with all the information without contributing their own analysis or delving deeper into what is required. This has limited the development of critical thinking and led to an increasing dependence on what is offered to them. As a result, in many cases, teachers have penalized such actions as inappropriate at different academic levels.

The pedagogical use of AI has become relevant to students and teachers in teaching and learning. However, among the limitations encountered are the prevalence of plagiarism and the difficulty in distinguishing between an original piece of writing and one produced by the tool. In addition, teachers face difficulties because they lack tools that facilitate this detection. Many of these tools are free but have limitations, and institutions have not opted to purchase the paid ones or make them available to their teaching staff.

The level of pedagogical use of generative AI by students is significant, and it has been demonstrated that the dimensions and indicators evaluated have real effects on learning, with broad potential to transform its application in higher education. This opportunity can be extended to include it in curricula as a collateral resource. However, this suggests that there is a difficulty in establishing guidelines on quality, ethics, and relevance criteria for implementation in the subjects that students must comply with, in addition to teacher supervision.

Given the proven impact of AI on learning in the classroom, educational institutions need to develop, implement, and monitor institutional policies that broadly allow for pedagogical use across curricular and academic activities. Special emphasis should also be placed on those who persist in making appropriate ethical use of these new technologies. The challenge here should focus on striking a balance between student autonomy in using the tools, critical training in their application in the academic sphere, and teachers' persistence in understanding their relevance to the development of their classes, their own training, and progressively expanding opportunities for improvement. This will allow for greater pedagogical use and greater ethical and responsible awareness among users.

AI offers various benefits and challenges. Despite this, current academic programs must be reviewed and adapted to new educational models that integrate digital tools and generative AI to maximize the potential for improving educational quality. However, it must be borne in mind that processes are advancing significantly, and the near future must take into account that the environment directly influences technological adoption, which calls for the creation of professional profiles with high standards and experience in the use of these technologies to improve their application in the academic field. Despite everything, the challenge is to ensure that experiences are equitable and accessible to all students. That is why educational institutions must have an investment plan for infrastructure, teacher training, and innovative curriculum design.

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# Chapter 06 / Capítulo 06

*New literacies in the age of AI: Ethics, teaching, and writing (English Version)*
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# Generative feedback: causal effects of LLM's on writing quality and evaluative equity in higher education

## Retroalimentación generativa: efectos causales de los LLM en la calidad de la escritura y la equidad evaluativa en educación superior

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### ABSTRACT

This chapter examines, within the framework of SDG 4, how large-scale generative *feedback* using large language models (LLMs) impacts the quality of scholarly writing and evaluative equity in higher education. The aim is to estimate improvements in coherence, argumentation, use of evidence, and clarity, and to determine whether gaps between subgroups (L1/L2, first generation, and baseline performance) are reduced. An experimental or quasi-experimental design (*stepped-wedge* cluster trial) with blinded assessment based on analytical rubrics and secondary metrics such as time to *feedback*, revision iterations, editing distance, self-efficacy, and teaching load is recommended. A synthesis of recent evidence suggests consistent gains when LLM *feedback* is effectively integrated into explicit rubrics and revision microtasks; furthermore, it increases engagement and can decrease inter-rater variability. However, risks of dependency, stylistic homogenization, and algorithmic bias are noted. Therefore, this chapter proposes a framework for didactic governance with traceability (registration of *prompts*, versions, and logs), open science principles (pre-registration, repositories), and a dual human-AI evaluation scheme with bias audits and human-in-the-loop thresholds. Among the limitations acknowledged are the heterogeneity of contexts, sensitivity to model versions, and external validity. The conclusion is that, under ethical safeguards and with teacher training, generative *feedback* can raise writing standards and broaden inclusion; further research is suggested on differential effects, disciplinary transferability, and institutional sustainability of scaling up.

**Keywords**: Evaluative Equity; Academic Writing; Large-Scale Language Models (LLMS); SDG 4 (Quality Education); Generative *Feedback*; Algorithmic Biases.

### RESUMEN

Este capítulo examina, en el marco del ODS 4, cómo la retroalimentación generativa a escala mediante modelos de lenguaje grandes (LLM) incide en la calidad de la escritura académica y en la equidad evaluativa en educación superior. El objetivo es estimar mejoras en coherencia, argumentación, uso de evidencia y claridad, y determinar si se reducen brechas entre subgrupos (L1/L2, primera generación y rendimiento basal). Se recomienda un diseño experimental o cuasiexperimental (ensayo por clúster tipo *stepped-wedge*) con evaluación ciega basada en rúbricas analíticas, y métricas secundarias como tiempo a *feedback*, iteraciones de revisión, distancia de edición, autoeficacia y carga docente. La síntesis de evidencia reciente sugiere ganancias consistentes cuando el *feedback* del LLM se integra efectivamente a rúbricas explícitas y microtareas de revisión; además, aumenta el involucramiento y puede disminuir la variabilidad interevaluador. Sin embargo, se advierten riesgos de dependencia, homogeneización estilística y sesgos algorítmicos. Por ello, el capítulo plantea un marco de gobernanza didáctica con trazabilidad (registro de *prompts*, versiones y logs), principios de ciencia abierta (pre-registro, repositorios) y un esquema de evaluación dual humano-IA con auditorías de sesgo y umbrales human-in-the-loop. Entre las limitaciones, se reconocen la heterogeneidad de contextos, la sensibilidad a versiones de modelos y la validez externa. Se concluye que, bajo salvaguardas éticas y formación docente, la retroalimentación generativa puede elevar estándares de escritura y ampliar la inclusión; se sugieren además, líneas futuras sobre efectos diferenciales, transferibilidad disciplinar y sostenibilidad institucional del escalamiento.

**Palabras clave:** Equidad Evaluativa; Escritura Académica; Modelos de Lenguaje a Gran Escala (LLM); ODS 4 (Educación de Calidad); Retroalimentación Generativa; Sesgos Algorítmicos.

## INTRODUCTION

The phenomenon of mass higher education and the growing diversity of students has highlighted a classic structural problem, namely the provision of timely, consistent, and highly personalized academic feedback (Wambsganss et al., 2022; Zhuang et al., 2025). It is precisely in the face of this practical impossibility of attending to a large cohort of students individually that the emergence of generative artificial intelligence (Gen AI) based on large language models (LLMs) offers a significant advance.

These systems promise to provide generative feedback at scale, meaning they generate automated comments rich in examples and concrete explanations of students' texts (Benner, 2024; Thomas et al., 2025). Such immediate and timely feedback can substantially improve the quality of student writing by clearly pointing out criteria for coherence, evidence, and clarity of argument. In addition, the uniformity of the criteria used by AI promotes evaluative equity, avoiding exclusions or inequalities, as all students receive the same level of attention regardless of their origin, gender, or social status, reducing traditional gaps (González et al., 2024; Jovic et al., 2025). This is where generative feedback represents a phase change, combining scalability and traceability of the evaluation process without sacrificing pedagogical specificity.

The relevance of this approach lies in two significant potential contributions. The first is that it can improve students' writing quality. In this regard, recent research has found positive effects on writing tasks when detailed automated feedback is incorporated. Wambsganss et al. (2022) observed that students who received automated argumentation feedback, along with a social comparison nudge, wrote much more convincing, better-structured texts.

Similarly, Glüsing et al. (2025) found in a randomized controlled trial (RCT) that individualized feedback generated by GPT-4 improved the quality of academic abstract reviews and increased students' review time. In contrast, in language learning environments, Zhuang et al. (2025) demonstrated that an adaptive AI system significantly raised the writing scores of hundreds of high school students, findings that are consistent and in harmony with those of Mekheimer (2025), who found that graduate students of English as a foreign language obtained significantly higher post-test scores-test scores and greater improvement in content, organization, and cohesion after using AI-assisted feedback.

Secondly, the contribution to evaluative equity is emphasized: by applying consistent criteria, AI can level the playing field for students with less linguistic proficiency or who are first-generation students, giving them access to the same constructive feedback as their more experienced peers, thereby reducing dispersion in results. This generates multiple effects, such as greater self-confidence and commitment reported by students after using AI tools, suggesting that these technologies can serve as uniform scaffolding.

This chapter aims to analyze in depth how generative feedback influences the quality of academic writing and evaluative equity, all within the framework of SDG 4 (Quality Education). To this end, we aim to evaluate how this type of feedback can not only assess but also improve writing quality, and then examine its impact on equity, particularly by reducing gaps associated with native language, initial performance, or first-generation status.

To this end, research questions are posed that focus on the impact on the quality of the written product, the timeliness and usefulness of the feedback generated, and the heterogeneity of effects among subgroups. Key concepts are operationally defined: generative feedback from AI-generated personalized feedback; writing quality, with the ability to argue coherently, with evidence and clarity; and evaluative equity, understood as the distributive justice of feedback in terms of access, timeliness, and uniform usefulness (Jovic et al., 2025). Notions of scaffolding (progressive educational support) and traceability (technical record of the feedback generation process) are also introduced to frame the methodological discussion.

To this end, a roadmap of the chapter is provided, developing the theoretical framework and empirical evidence on automated feedback; then a methodological design with recommended experimental approaches is proposed; a synthesis of results is presented; pedagogical and institutional implications are discussed; ethical considerations and academic integrity are addressed; and finally, limitations and the future agenda are outlined.

## DEVELOPMENT

### Conceptual framework

From a theoretical perspective, the literature highlights the importance of self-regulated learning and iterative writing to improve writing performance. The self-regulated learning model (Zimmerman, 2000) implies that students plan, monitor, and evaluate their own writing process. In feedback environments, the authors point out that feedback-based revision tasks are highly self-regulated, as students must use cognitive and metacognitive strategies to incorporate suggestions (Alcudia Ólan & Morales Vázquez, 2025). Tian & Liu (2022) show in their research that when receiving feedback, whether automatic, from peers, or from teachers, writers deploy various regulation strategies (planning or self-revision) to improve their texts. This suggests that well-designed, immediate, and actionable feedback stimulates the self-regulated cycle of; conversely, insufficient feedback greatly hinders self-revision.

In line with Hattie & Timperley (2007), feedback is most effective when it is immediate, accurate, and elaborative. For example, feedback that not only points out errors but also explains their correction and provides concrete examples produces greater learning gains. In this sense, the generative feedback of LLMs can act as a cognitive scaffold in that the models can provide specific examples and explanations, which help students compare their writing with established criteria in terms of argumentation, evidence, and clarity, but above all, to rewrite more effectively (Quesada & Salinas, 2021).

Furthermore, as it is an automated process, it provides actionable, consistent feedback, ensuring that all students receive guidance based on an explicit analytical rubric that defines observable indicators. This methodological consistency of automated feedback also points to equity, as applying the same standards uniformly seeks to minimize human bias.

The concept of evaluative equity is understood here as the distributive justice of feedback, grounded in equal accessibility and utility. This implies that all students, regardless of their profile or sociocultural conditions, have equal access to relevant and timely comments. In practical terms, equity metrics include reducing both absolute and relative gaps in written results between these groups. The literature on assessment has suggested that equity does not always imply equal results, but rather a fair application of criteria (Romero-González, 2024).

Jovic et al. (2025) define equity as the fairness and consistency of feedback across different groups of students, whether native or non-native speakers. Based on the precepts of these authors, an automated feedback system must record indicators such as response time to feedback and variability in subgroup improvements, which are crucial for identifying whether existing disparities are effectively reduced.

LLMs also function as educational technology with their own potential and limitations. Among their advantages is the ability to dynamically scale feedback to fit the student's text. However, recent studies warn that these systems require human supervision. For example, evidence indicates that conversational prompting (guiding the LLM with specific questions) can improve the quality of feedback. However, LLMs frequently exhibit flaws such as hallucinations (inventing nonexistent content) or generic responses when faced with more complex arguments (Sandoval et al., 2024).

Therefore, given this scenario, it is necessary to integrate clear rubrics, guided review tasks, and validation by human experts so that AI serves to complement, rather than replace, teachers' work (Valenzuela & Pérez, 2025). Similarly, the traceability of the process through the recording of prompts, model versions, and usage logs is key to auditing and correcting algorithmic biases, as well as adjusting thresholds or levels of human intervention. In this context, generative feedback is an innovative pedagogical resource. However, in order to guarantee educational quality, it must be embedded in supervisory structures to ensure relevance and fairness in assessment (Xia et al., 2024).

Empirical research on generative feedback in higher education has recently expanded. To date, several studies have shown that automated feedback improves writing quality and the efficiency of the feedback process. In their study of 124 students, Wambsganss et al. (2022) found that those who received automated argumentation feedback combined with a social comparison incentive significantly improved the quality of their argumentative texts compared to control groups (Afrin et al., 2021). Quasi-experimental studies, such as the one developed by Glüsing et al. (2025), have confirmed that students who received feedback from GPT-4 achieved higher-quality revisions of research abstracts and showed greater behavioral engagement in the task (more revision time, more editing distance) than a group without automated feedback.

In the context of language teaching, the study developed by Zhuang et al. (2025) reports statistically significant improvements in the writing scores of secondary school students after using a multimedia AI system for adaptive feedback. Similarly, Mekheimer (2025) found that English as a foreign language (EFL) students who received AI-assisted feedback from Grammarly outperformed the control group on writing tests. In addition, they revised their texts more frequently and reported greater satisfaction and confidence in the process.

This body of evidence, as suggested by Gombert et al. (2024), demonstrates that generative feedback, when properly designed, can significantly improve the revision cycle and enhance writing quality. Furthermore, immediate feedback availability reduces students' waiting time, which is crucial in large-scale courses with high enrollment. It should be noted that, in general, students have rated AI-generated feedback positively, especially when it is perceived as specific and relevant to their learning process (Thomas et al., 2025).

In contrast, research on heterogeneous effects is still in its infancy, as few studies have systematically examined how these interventions benefit subgroups differently. However, Jovic et al. (2025) observe that AI-generated responses tend to be more consistent across students from different backgrounds, though they lack depth in analyzing complex arguments.

According to the evidence presented in this research, the gaps to be closed include validating the fairness of feedback algorithms, given concerns about the replicability of data biases, and ensuring explicit traceability to audit for possible favoritism. Precisely in this context, the state of the art suggests that generative feedback can improve learning, reducing existing disparities in a scalable manner. However, more causal and analytical research by subgroups is still needed. Therefore, the research will add value by explicitly focusing on a causal and equitable approach, as well as on the institutional dimensions of scaling and the governance of automated feedback, aspects that have been little explored until now.

**Recommended methodological design for generative feedback**

To rigorously evaluate the effects of generative feedback, an empirical experimental or quasi-experimental design in real higher education settings is recommended. Specifically, a cluster trial or stepped-wedge design balances internal validity and logistical feasibility (Chen et al., 2021). For example, several university courses or subjects with similar written assignments (taught by cohort or class) could be selected and randomized by groups or sequences to receive the intervention.

The control condition would correspond to the usual feedback method (professor or manual corrections). At the same time, the treatments would include at least two variants, namely: 1) LLM + structured rubric, and 2) LLM + rubric + guided review microtasks (explicit scaffolding). The target population would be undergraduate students in writing courses or subjects with substantial written components, preferably large and diverse samples to ensure greater statistical power and better subgroup analysis.

The primary results would be writing quality metrics obtained through blind evaluation with an analytical rubric, which would include key criteria such as argumentation (coherence of the thesis and its corresponding logical structure), textual coherence, use of evidence, and expressive clarity, which must be consistent with pedagogical standards (Glüsing et al., 2025). These rubrics should be developed based on previous literature on good writing practices and, as far as possible, adapted by expert linguists or teaching professionals prior to the study.

In addition, secondary outcome indicators will be collected, such as: time from text submission to receipt of feedback (to measure timeliness), number of revision iterations performed by the student, editing distance (quantitative measure of how much the text changes after feedback), writing self-efficacy (student surveys on their confidence), and perception of teaching load (questionnaires to teachers about supervision effort); these outcomes will cover both effectiveness and efficiency dimensions.

To assess equity, an analysis of effect heterogeneity would be performed. The sociodemographic data to be included would include native language, first-generation status, baseline performance decile or quartile, and gender, among others deemed relevant. Average effects (ATE) and conditional effects (CATE) will be estimated using statistical models that allow for interactions, such as regressions with subgroup dummy variables and their interactions with treatment (Holgersson et al., 2015).

In particular, we will examine whether treatment with generative feedback significantly reduces the score gap between groups relative to the control, as would be expected with changes in the absolute and relative differences in means between students at one level (L1) and students at a higher level (L2). The statistical analysis will use multilevel models (e.g., with students at level 1 and sections/classes at level 2) to control for hierarchical dependence in the data (Impey et al., 2025). Statistical correction methods for multiple comparisons (e.g., Bonferroni or FDR) will be applied when testing multiple outcomes, and effect sizes and confidence intervals will be calculated to assess practical magnitudes (Ren & Ren, 2025).

As a good practice in open science, it is recommended to pre-register the research protocol, for example by following CONSORT-AI for AI interventions (Chen et al., 2025), and to provide a public repository with anonymized materials and data such as prompts, LLM model version, hyperparameters used, complete rubrics, analysis scripts, and interaction logs (sequences of prompts and responses). This transparency facilitates reproducibility and future bias auditing.

**On the presentation of results and synthesis of evidence**

The results section would present both a descriptive and inferential synthesis of the findings. First, the researcher must describe the sample: the number of students, distribution by key characteristics (native language, gender, among others), and the baseline or reference point used to determine writing quality (initial scores). Previous studies have observed initial variability that justifies baseline controls (Wambsganss et al., 2022).

Next, the main effects of LLM treatment versus control on writing quality and time would be shown. For example, statistically significant and practically relevant increases in blind quality scores would be expected; the effect size (Cohen's d) would be interpreted in pedagogical terms, considering how much the average writing score improves (Sullivan & Feinn, 2012). Likewise, the change in feedback time would be evaluated; ideally, students in the LLM group would receive almost instantaneous corrections (close to zero), in contrast to the days or weeks in the control group.

Regarding differential effects, we would report how feedback influences each subgroup. In this case, we would examine whether the absolute gap between students at level 1 (L1) and level 2 (L2) in writing scores is reduced after receiving generative feedback (indicating greater equity). Differences across initial quartiles would also be analyzed to determine whether some groups obtain greater benefits or, conversely, whether the intervention maintains uniform improvements (a desirable situation for equity).

In similar studies (Jovic et al., 2025), greater relative gains are sometimes observed in traditionally disadvantaged groups, as AI can raise the lowest base. However, the possibility of reverse bias will also be considered when LLMs privilege the linguistic patterns of native speakers, for example, in second-language learning. Complementarily, the robustness of these results would be evaluated through a sensitivity analysis and controls for contamination between groups to prevent the control group from receiving additional feedback.

Subsequently, complementary indicators would be presented, such as when, in the experiment by Glüsing et al. (2025), feedback from the LLM increased editing time (an indicator of engagement), which in turn mediated higher revised quality. Student assessments of the usefulness of feedback (using Likert scales) would also be reported to understand the perception of usability. All tables would include 95 % confidence intervals for estimated effects and statistical criteria (p-value, effect size). In this way, the section would summarize the key findings, namely changes in blinded quality scores and response times, along with the reduction or increase in gaps between subgroups, based on the interpretation of practical magnitudes.

The hypothetical findings described would have several pedagogical and, obviously, institutional implications. First, a positive effect on writing quality would indicate that generative feedback acts as effective cognitive scaffolding. This can be interpreted through self-regulated learning mechanisms when receiving explanations and examples, whereby students assimilate explicit criteria (metacognition) and improve their writing in successive iterations.

The results of Wambsganss et al. (2024) show that the motivational component (social nudge) combined with explicit feedback triggered favorable psychological processes (self-efficacy, motivation). Similarly, the use of specific examples in feedback (content generated by an LLM) provides direct scaffolding, as the student sees models of argument structure or appropriate citations, which facilitate rewrites. In practice, this suggests that AI-based pedagogical interventions should include prompts that generate clarifications and concrete examples, rather than merely making general observations.

In terms of equity, the results indicate the extent to which technology leveled the playing field. A finding of reduced gaps between L1 and L2 students, or greater improvements in the first deciles, would support the idea that AI can promote distributive justice. However, this should be interpreted with caution: the internal validity of the experiment (randomization, control) strengthens the causal inference from these average effects, but generalizability (external validity) will depend mainly on the institutional context. For example, if the study were conducted in universities with high technological infrastructure, its transfer to universities with fewer resources would require adaptations. Similarly, consistency in causal inference is reinforced by the multilevel design and rigorous analysis applied (Impey et al., 2025), but the variability of LLMs, whether due to the emergence of new versions or changes in prompts, may limit exact replicability.

In any case, the results would have obvious implications: if generative feedback demonstrates transparency and robustness, its institutional deployment would be recommended. This implies, first of all, the implementation of AI-based teaching co-pilots to assist students and teachers, such as writing chatbots, review assistants, or AI agents. In addition, to enhance these results, institutions will need to invest in teacher training, teaching teachers how to interpret and complement automated feedback and how to use traceability dashboards to see what feedback was given.

Secondly, from a governance perspective, it would be necessary to define continuous improvement protocols that periodically review prompts and adjust the system based on actual performance data. In short, this is a systemic approach to decision-making that, being data-driven, would be key, leveraging feedback log analytics to refine teaching policies and thus ensure writing excellence through deeply responsible AI.

**Ethical considerations, integrity, and traceability**

The use of AI in education poses significant ethical and academic integrity challenges that must be explicitly addressed. In terms of ethics and privacy, students' informed consent must be obtained to process their writing with AI, ensuring, above all, that the data is anonymized. In addition, the principle of minimization must be applied, meaning that only the information strictly necessary to evaluate the system's effectiveness should be collected, and personal identifiers should be removed. Similarly, students who choose not to participate must be guaranteed equivalent support with manual feedback, without any reprisals or sanctions.

In terms of academic integrity, it is crucial to emphasize students' active role in creating their writing. While it is true that AI will provide feedback, the final intellectual work belongs to the student and is their intellectual production. Human authorship is therefore promoted, and AI systems should not be listed as authors in any derivative product. This starts with requiring students to declare the use of AI tools in their processes to safeguard transparency. In addition, it is advisable to integrate training modules on the responsible use of AI, emphasizing that AI is an assistant, not a substitute for critical-analytical thinking. Mekheimer (2025) found that students emphasize the need to avoid over-reliance on AI and, for this reason, the study documentation will require reinforcing digital and ethical literacy, prioritizing critical thinking skills even when AI is used.

Regarding technical traceability, detailed metadata must be recorded for each feedback cycle, including the prompts used with the LLMs, the model version, the generation parameters, and interaction logs, without including personal information. This will facilitate auditing for biases, allowing scenarios to be rerun if the model shows unfair responses.

This starts with establishing a review threshold: when the AI detects ambiguities or inconsistencies in a text, it automatically activates human intervention ("human-in-the-loop"), so that a teacher can review or supplement the feedback. In addition, at this point, it would be desirable to apply periodic bias audits to the system, as suggested by guidelines for responsible AI in education, to identify discriminatory patterns (UNESCO, 2024), since transparency and traceability are what guarantee that the use of AI does not compromise the equity or quality of teaching, in line with international ethical standards.

Like any study, the proposed research has limitations. First, specific data and contexts, such as courses, subjects, institutions, and cohorts, may limit generalizability. The results will depend on the LLM model version available during the experiment phase, and future updates to the model could alter the effectiveness of the feedback (Saini et al., 2024). In addition, the measurement of writing quality would depend on the reliability of the analytical rubrics. Although the grading will be shielded, there will always be room for subjectivity. Moreover, in terms of equity, the categories analyzed for L1 and L2 student levels may be correlated with unobserved factors, such as socioeconomic status, which would complicate the interpretation of the gaps.

It is important to emphasize that the chapter proposes a future agenda to deepen these explorations. Therefore, longitudinal follow-ups are recommended to assess whether writing improvements persist over time or accumulate with continuous feedback. It would also be valuable to extend the study to other disciplines where writing has very different functions. The integration of this feedback with broader learning analytics can enrich the understanding of the mechanisms of change. In view of this, it is suggested that the cost, benefits, and institutional effectiveness be evaluated, because although the technology promises scalability, its implementation requires investment in infrastructure and teacher training, a factor of great importance for sustainable adoption within the framework of SDG 4.

## CONCLUSIONS

The evidence gathered shows that LLM-powered generative feedback has considerable potential to improve writing quality in secondary and higher education by providing detailed, timely comments that leverage students' self-regulated learning. Likewise, this approach can contribute to greater evaluative equity by applying consistent criteria, thereby reducing baseline disparities between groups and expanding access to meaningful feedback. However, it is important to note that these positive effects depend on careful design that requires human oversight and transparent architecture to avoid automatic biases, as the current literature still lacks robust research on the precise differential effects by subgroups and on large-scale institutional deployment.

As recommendations, teachers and curricula are urged to adopt AI-assisted teaching gradually; this involves defining clear adoption criteria, such as explicit rubrics, and training teachers to interpret automated feedback. At the institutional level, scaling should be planned with continuous auditing by educational AI ethics committees, and the AI strategy should be linked to the equity goals established in SDG 4. Above all, the latent need to continue generating scientific evidence is emphasized, stemming from the creation of university research networks that share data in a protected manner and document their lessons learned.

Finally, and looking ahead to the roadmap for the remaining years to reach the 2030 agenda deadline, this chapter envisions a future in which writing excellence and equity are enhanced by responsible AI. To achieve this, iterative improvement paths must be mapped out that monitor new LLM developments, integrate automated feedback into curricula, and train the entire academic community in its critical use. Only then can the quality education envisaged in SDG 4 achieve its goal of relevant and effective learning for all students, driven by scalable and equitable feedback.

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# Chapter 07 / Capítulo 07

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# Impact of generative AI on the ideation phase of strategic planning

## Impacto de la IA generativa en la fase de ideación de la planificación estratégica

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**ABSTRACT**

This qualitative research is based on grounded theory methodology with a rigorous, comparative analysis. It is noteworthy that its purpose is to analyze the impact of generative Artificial Intelligence (AI) on the quality, diversity, and viability of strategic options co-created by university planning teams. Currently, the use of strategic planning is crucial for organizational survival and growth (Porter, 1985), and it also faces the challenge of diminution due to cognitive biases and traditional approaches when innovating in the ideation and formulation stages (Kahneman & Tversky, 1979). Likewise, Generative Artificial Intelligence (GAI) presents an emergence, representing a technological disruption offering new strategic options (Brynjolfsson & McAfee, 2014). In turn, through in-depth interviews and thematic analysis, the perceptions and experiences of academic leaders and planners were examined. To achieve the aforementioned objectives, specific objectives were achieved, such as: identifying the main use cases as a “disruptive idea engine” and simulating feasibility scenarios. However, this research achieves cognitive advancement, which creates tension in team dynamics, changing the role of the planner to that of a “strategic curator,” posing challenges regarding authorship and intellectual property of ideas. In conclusion, the increase in strategic potential is due to generative AI; long-term success will depend on universities’ ability to effectively manage the new cultural, ethical, and governance challenges posed by human-machine co-creation.

**Keywords:** Artificial Intelligence; Ideation; Strategic Planning.

**RESUMEN**

Esta investigación cualitativa está sustentada en la metodología de la teoría fundamentada con un análisis comparativo y riguroso. Es de hacer notar que tiene como fin el análisis del impacto de la Inteligencia Artificial (IA) generativa en la calidad, diversidad y viabilidad de las opciones estratégicas co-creadas por equipos de planificación universitaria. En la actualidad es de carácter decisivo para la supervivencia y el incremento organizacional, el uso de la planificación estratégica (Porter, 1985), así mismo también se enfrenta el desafío de la disminución por sesgos cognitivos y enfoques tradicionales al innovar en las etapas de ideación y formulación (Kahneman & Tversky, 1979). Así mismo, la Inteligencia Artificial Generativa (IAG) presenta una emergencia lo que representa una disrupción tecnológica ofreciendo nuevas opciones estratégicas (Brynjolfsson & McAfee, 2014). A su vez, mediante entrevistas a profundidad y análisis temático, se examinó las percepciones y experiencias de líderes académicos y planificadores. Para lograr lo anteriormente descrito se sustentó en cumplir objetivos específicos, tales como: Identificación de las modalidades de uso principales como el “motor de ideas disruptivas” y la “simulación de escenarios de viabilidad". Sin embargo, esta investigación logra el avance cognitivo lo cual genera una tensión en la dinámica de equipo, modificando el rol del planificador a un "curador estratégico", planteando desafíos de autoría y propiedad intelectual de las ideas. En conclusión, el aumenta el potencial estratégico es debido a la IA generativa, el éxito a largo plazo dependerá de la capacidad de las universidades para gestionar efectivamente los nuevos retos culturales, éticos y de gobernanza que implanta la co-creación humano-máquina.

**Palabras clave:** Inteligencia Artificial; Ideación; Planificación Estratégica.

## INTRODUCTION

Strategic planning is the primary mechanism for an organization's adaptation and success (Porter, 1985). It should be emphasized that the ideation phase is critical for generating novel and disruptive options. However, cognitive biases and the rigidity of traditional methods are the result of process barriers (Kahneman, 2011). On the other hand, a powerful tool for co-creation at the service of strategy is offered, allowing a universe of possibilities to be explored at unprecedented speed through the emergence of Generative Artificial Intelligence (GAI) using advanced language models (Brynjolfsson & McAfee, 2014). GAI plays a fundamental role in the quality, diversity, and viability of strategic opportunities generated by human teams, with impact analysis.

University strategic planning has resurfaced amid rapid change, with institutions facing unprecedented challenges that require superior agility and foresight (Mintzberg, 1994). Traditionally, in this process, human cognition has relied heavily on the ideation phase, which is limited to the experiences and inherent biases of leadership teams (Kahneman, 2011).

Generative Artificial Intelligence (GAI) has been significantly transforming strategic planning processes, thereby serving as a device for organizational adaptation and acceptance (Porter, 1985).

Traditionally, the ideation phase was part of human cognition, which is inherently biased and limited, but advanced language models (Kahneman, 2011) can overcome these limitations. However, with the emergence of GAI, this is a powerful tool for strategic co-creation. It should be recognized that it allows for the deepening of an extensive universe of capabilities, accumulating massive volumes of data to simulate scenarios and generate disruptive options (Brynjolfsson & McAfee, 2014).

In this context, AI acts as a "cognitive co-pilot" that should not be compared to human decision-making, increasing the quality, diversity, and viability of strategic ideas (Davenport et al., 2023). In the university setting, it is essential to confront the challenges posed by rapidly changing circumstances, where technological disruption and new labor-market demands require agility and a highly forward-looking vision (Mintzberg, 1994). The adoption of IAG by academic planning groups becomes a crucial research objective, seeking to examine how this instrument defines creativity and decision-making, and how its integration promises a prototype of adaptive, forward-looking governance.

However, systems capable of producing novel and coherent content are the product of the maturity of generative Artificial Intelligence (AI), which can shift how institutions conceive of their future. Tools can enhance strategic creativity (Davenport et al., 2023) by analyzing large volumes of internal and external data, enabling the simulation of future scenarios and the generation of disruptive strategic options. This is an observation that human planners might overlook (Susskind & Susskind, 2020).

The practices of adopting generative AI by planning teams aim to determine the magnitude, modalities, and ethical implications. The aim is to establish how this technology influences the quality, originality, and speed of the strategic ideas produced, and whether its integration leads to a more forward-looking and adaptive model of academic governance. More specifically, the goal is to provide a robust analytical framework for effectively integrating generative AI into the core of academic leadership and management to fill an empirical gap.

## DEVELOPMENT

Strategic planning has traditionally been defined by authors such as Porter (1985) in terms of competitive advantage and positioning, or by Mintzberg (1994), who criticized its excessive formality and advocated a more emergent, flexible approach. The ideation or option formulation phase is critical but intrinsically vulnerable to cognitive biases that limit the exploration of novel alternatives (Kahneman, 2011). Therefore, any tool that mitigates these biases and broadens the spectrum of options is relevant. The challenge is to assess whether technological assistance promotes genuinely strategic creativity or merely generates an “illusion of diversity.”

The advent of generative artificial intelligence (GAI), primarily through Large Language Models (LLMs), has radically changed the way content is created and problems are solved. Brynjolfsson and McAfee (2014) point out that these technologies are transforming tasks, noting that collaboration between people and machines will be fundamental in what they call the “second machine age.” The main idea is that GAI helps to expand options and think outside the box, although the quality and feasibility of these ideas still need to be analyzed and validated by humans in each context.

Susskind & Susskind (2020) argue that digital disruption requires examining models of academic leadership and strategic planning. Regarding the empirical gap in understanding how generative Artificial Intelligence (AI) impacts the quality and dynamics of strategic ideation in higher education, a sector characterized by institutional inertia, Mintzberg (1994) points out that it does so. Similarly,

Davenport et al. (2023) recognize that the potential of AI remains unexplored in the university context, thereby increasing operational efficiency and its role in disruptive strategy and the generation of strategic knowledge.

The theoretical framework for this research is based on an approach to three essential pillars:

1. Strategy and its development: Analyzes Strategy Theory, understanding it from a design to a cognitive approach, establishing ideation as a process that combines logic and intuition.
2. Technology-Assisted Cognition: Examines the interaction between human and algorithmic (AI) abilities, with the application of Artificial Intelligence functioning as a “co-pilot” that helps reduce cognitive biases such as anchoring and confirmation (according to Kahneman, 2011).
3. Ethical Regulation of AI in Education: Covers the governance of Artificial Intelligence, focusing on the ethical, equity, and transparency implications of making strategic decisions with algorithmic support.

The research goes beyond a mere technical analysis of Generative Artificial Intelligence (GAI). Its purpose is to elucidate the profound organizational and cultural effects resulting from its integration into the university environment.

The expected results are:

1. Theoretical value to the discipline of strategic university management.
2. A practical and responsible model for the adoption of GAI.

This framework seeks to enhance the vision of the future and strengthen institutions' adaptability in the 21st century.

Research on the Impact of Generative AI on University Strategic Ideation requires an active, committed methodology that goes beyond passive measurement to seek reflective intervention and transformation in the real-world environment of university management.

**Qualitative Approach**

Depth and Human Meaning. This research, rooted in the qualitative paradigm (Creswell & Creswell, 2018), aims to investigate the depth, context, and human meaning of the phenomenon. In determining this, the introduction reorganizes thinking, creativity, and power dynamics within the strategic planning process. To achieve this rich, context-rich learning, the methodological development is critically directed at the expectations of key actors: leaders, planners, and academics who experience the tension and potential of AI in decision-making.

**Research Design**

*Voice and Contrast of Experiences:* the research project is based on Grounded Theory (Corbin & Strauss, 2015) using a Case Study approach, which allows for deep immersion:

*Case Study as Living Narrative:* three universities were selected not as objects of study, but as institutional settings with different cultures of technological maturity and AI governance models. The objective was to link the wealth of experiences and contrasting perceptions (Yin, 2018) between institutions that are just adopting AI and those that have integrated it ethically.

*Theory for Interpretation:* this perspective ensures that the theory emerging from the study is not imposed but is built inductively from the voices, dilemmas, and practices of the actors. This argument supports the ecological validity of the findings and resonates with the human complexities of strategic ideation.

Semi-structured interviews were used as a data collection technique, focusing on interviews with high-level leaders and members of strategy teams. The questions explored experiences with generative AI, the meaning attributed to it, and how this technology reconfigures power dynamics and the culture of ideation. Additionally, documentary analysis of meeting minutes or draft strategic plans was used to contextualize the actual use of AI.

The information was analyzed using thematic analysis to identify patterns and emerging categories, and to develop a conceptual framework to understand the interaction between generative AI and strategic cognition. Rigor was ensured through the triangulation of sources and participants' verification that the interpretations reflect the realities of the institutions studied. The final product was an understanding of the transformation of university strategic ideation through this new technology.

The research on the impact of generative AI on the ideation phase of strategic planning used a qualitative methodology, specifically Grounded Theory (GT).

This theory is justified by its ability to build a theory from data, rather than testing a pre-existing theory. This perspective is suitable for delving deeper into an emerging phenomenon, such as the integration of generative AI into strategic planning, discovering the dynamics, processes, and experiences in which the actors involved coexist. This methodology is iterative and reflective, and FT aligns well with the need to understand how this new technology is reconfiguring ideation practices in institutions, beyond what the current literature provides.

**Sample and Theoretical Sampling**

The sampling process was carried out as follows:

1. *Implementation:* The researcher began with a general notion of purposive sampling. The first key informants were identified in academic institutions that have experimented with generative AI tools across various strategic processes.
2. *Iteration and* adjustment: Initial data were collected and analyzed through semi-structured interviews and document analysis, yielding conceptual categories. These categories led to the selection of subsequent informants.
3. *Theoretical finding:* The theory is developed with the contribution of the categories. Subsequently, confirming and disconfirming cases were observed, which contributed to conceptualizations and strengthened the emerging theory.

**Qualitative Data Analysis**

Data analysis was carried out in conjunction with data collection, with constant comparison, a characteristic method of Grounded Theory. It should be noted that the coding process will be carried out in several stages:

1. *Open coding*: The interviews and documents were broken down line by line, *identifying* and labeling key concepts. Initial labels were created to reflect the participants' experience and language.
2. *Axial coding*: At this stage, connections were established between the categories. Within the categories, it was possible to relate and highlight causes, consequences, context, and strategies used by the informants.
3. *Selective coding:* A central category was then determined that integrates all the others, constructing a coherent theoretical narrative that explains the impact of generative AI on strategic ideation. This process led to analytical memos that documented the researcher's written reflections.

**Limitations of the Methodology**

It should be noted that among the limitations encountered are:

1. Biases may influence the way categories are constructed.
2. Validity depends on the emerging theory's capacity.
3. A thorough analysis was carried out to ensure that no important information or perspectives were overlooked.

The choice of Grounded Theory provided detailed research into the complex and dynamic impact of generative AI in the strategic ideation phase, allowing for an assimilation of the phenomenon from the perspective of the actors themselves.

Likewise, the findings were related to the observations themselves and to the studies of interest, pointing out their contributions and limitations without reiterating data already discussed in other sections. The inferences from the findings and their limitations should be presented, including implications for future research, and the conclusions should be linked to the study's objective, avoiding gratuitous statements and conclusions that are not fully supported by the data.

The qualitative thematic analysis, based on the direct voice of university leaders and planners, has revealed the complexity of the impact of generative AI. The findings demonstrate the technical description and how the technology performs cognition, team dynamics, and ethical structures, thereby validating the quality, diversity, and viability of co-created strategic options.

**1. Modalities of Use: AI is a "Human Vision Accelerator."**

Teams is a high-level strategic assistant. With three functions that demonstrate a symbiosis:

- *Generation of* Disruptive *Options*: AI is a creative catalyst, with solutions to propose new models of organizational programs.
- *Strategic Impact Simulation*: The tool is an accelerated financial viability projection that provides the team with feedback on the potential consequences of their ideas.
- *Mapping Global Trends*: AI reduces the time needed to identify labor market needs and educational trends, freeing leadership to focus on interpretation.

Finally, AI increases leaders' scouting capabilities, freeing up their cognitive capital for strategic judgment and value-based decision-making.

**2. Cognitive Changes and Team Dynamics: Empowerment and Intellectual Property.**

The introduction of AI has had a polarizing impact on the human capital of the strategy, where the following could be observed:

- *Cognitive Benefit (Quality):* AI combats inertia in strategic thinking, reducing confirmation bias and increasing the diversity of initial ideas.
- *Tension in Dynamics (Ownership)*: A crucial division was observed. Technophiles feel creatively empowered. However, other members reported a sense of "loss of intellectual property" or authorship over the ideas generated.

The challenge lies in managing authorship and ownership. It is important to establish new policies that ensure creativity is a collective achievement.

**3. Challenges and Governance: Trust, Legitimacy, and Algorithm Ethics**

The final problem with AI adoption is the institutional resources and ethical legitimacy of strategic decisions: The Need for Enhanced Ethical Governance. The way to overcome this "legitimacy crisis" is through action. "Enhanced Strategy Audit Committees" must be created.

Ultimately, Susskind & Susskind (2020) point out that the long-term viability of generative AI depends on whether the institution manages to engage with the technology by enhancing human vision with inclusion, equity, and transparency, rather than nullifying it with incomprehensible opacity. Improvements in ideation lie in ethical and governance frameworks and in safeguarding the human essence of decision-making (table 7.1).

| Specific Objective | Emerging Central Category (Substantive Theory) | Key Subcategories/ Properties (Axial Coding) | Consequences/Explained Phenomenon (Related to Ideation) |
|---|---|---|---|
| **Analyze the impact of using generative AI on the quality of co-created strategic options.** | A. Transformation of the Strategic Quality Standard | A.1. Analytical Depth: Greater or lesser rigor in the base diagnostic. | AI raises the "acceptable" threshold, forcing human teams to focus on contextual viability and ethical judgment beyond mere logic or coherence. |
| | | A.2. Internal Coherence: Degree to which options align with mission and resources. | Breakdown of cognitive biases in formulation, but risk of homogenization if AI is not guided by diverse prompts. |
| | | A.3. Empirical Foundation: Speed and breadth of data support for the option. | Trust in the source of the AI's input (transparency) becomes a critical factor of perceived quality. |
| **Analyze the impact of using generative AI on the diversity of co-created strategic options.** | B. Expansion of the Cognitive and Thematic Horizon | B.1. Thematic Scope: Inclusion of previously unconsidered topics (e.g., emerging risks). | AI acts as a "provocateur agent," injecting "disruptive ideas" or "outside perspectives" (e.g., from other sectors) that break the inertia of university strategic thinking. |
| | | B.2. Variability of Approaches: Number of conceptual frameworks or strategic paradigms used. | The ease of generation drives a larger quantity of initial options (volume), but the challenge lies in managing information overload. |
| | | B.3. Inclusion of Voices: Reflection of external or minority perspectives in the options. | A "democratization of inspiration" is observed by allowing less experienced members to contribute robust options thanks to AI support. |
| **Analyze the impact of using generative AI on the viability of co-created strategic options.** | C. Reconfiguration of the Evaluation and Validation Process | C.1. Operational Realism: Estimation of necessary resources, time, and infrastructure. | AI accelerates pre-validation, filtering out unfeasible options in early stages by simulating scenarios, which reduces ideation time and increases team efficiency. |
| | | C.2. Risk and Resilience: Early identification of threats and mitigation plans. | Human teams reorient their effort from basic creation towards critical evaluation, fine-tuning, and political negotiation of the generated options. |
| | | C.3. Stakeholder Acceptance: Perception of the options by the university community. | A new reliance on AI's predictive capabilities emerges, but the need for the "Human Seal" remains to legitimize and obtain the community's commitment. |

**Table 7.1.** Analysis of responses

## CONCLUSIONS

The integration of generative AI is of great importance in the ideation phase of university strategic planning, as it represents a turning point by increasing the quality and diversity of strategic options, placing critical demands on governance and academic leadership.

AI has shifted from being an analytical tool to becoming an "engine of strategic co-creation." Likewise, key uses such as the reproduction of disruptive program models and feasibility simulations confirm the broadening of the institution's strategic horizon. A cognitive transformation in teams is confirmed.

AI reduces human bias by considering radical strategic options. However, the improvement in strategic quality creates cultural tension, with the change in the planner's role to "strategic curator" marking a milestone in the authorship of ideas.

Finally, one limitation is emphasized: the ideas generated by AI regarding strategic viability are intrinsically linked to their legitimacy. Algorithmic opacity and the need to audit input data are perceived as direct threats to inclusion and transparency in decision-making. In conclusion, the positive impact of generative AI will be realized if universities establish ethical governance and transparency frameworks grounded in accountability, thereby transforming AI from a technical tool into a reliable strategic partner.

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# Chapter 08 / Capítulo 08

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# From Plagiarism to Process Transparency: Redefining Student Authorship in Light of International and Comparative Copyright Law

## Del Plagio a la Transparencia de Proceso: Redefiniendo la Autoría Estudiantil a la Luz del Derecho de Autor Internacional y Comparado

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### ABSTRACT

This paper analyzed the tension between the use of generative artificial intelligence (GAI) by students and legal and academic frameworks based on human authorship. A doctrinal analysis of international and comparative copyright law was conducted to demonstrate that GAI is inherently incapable of being recognized as a co-author, and that this legal vacuum is not a flaw but a structural limitation of the system. Given this regulatory inability, it was argued that the educational community must transcend the legal debate and generate new ethical-pedagogical frameworks. As a solution, it was proposed to redefine “student authorship,” shifting the focus of evaluation from the final product to the writing process. The study concluded that implementing a model of “process authorship,” centered on transparency, critical curation, and reflection, represents a pedagogical opportunity to prepare students for an environment of co-creation with machines, overcoming the limitations of AI detectors and prohibitive policies.

**Keywords:** Generative Artificial Intelligence; Law; Authorship; Transparency; Academic.

### RESUMEN

Este trabajo analizó la tensión entre el uso de inteligencia artificial generativa (IAg) por estudiantes y los marcos legales y académicos basados en la autoría humana. Se realizó un análisis doctrinal del derecho de autor internacional y comparado para demostrar que la IAg es inherentemente incapaz de ser reconocida como coautora, y que este vacío legal no constituye una falla sino un límite estructural del sistema. Ante esta incapacidad regulatoria, se argumentó que la comunidad educativa debe trascender el debate jurídico y generar nuevos marcos ético-pedagógicos. Como solución, se propuso redefinir la “autoría estudiantil”, desplazando el foco de la evaluación desde el producto final hacia el proceso de escritura. El estudio concluyó que implementar un modelo de “autoría de proceso”, centrado en la transparencia, la curación crítica y la reflexión, representa una oportunidad pedagógica para preparar a los estudiantes para un entorno de co-creación con máquinas, superando las limitaciones de los detectores de IA y las políticas prohibitivas.

**Palabras clave:** Inteligencia Artificial Generativa; Derecho; Autoría; Transparencia; Académico.

## INTRODUCTION

The emergence of generative artificial intelligence in classrooms has triggered a fundamental paradox for higher education: students use tools such as ChatGPT, Gemini, or DeepSeek as collaborators in the writing process, while existing legal and academic frameworks cling to a concept of individual and human authorship that fails to capture this new reality.

This tension between the emerging practice of co-creation with AI and outdated regulatory systems—from intellectual property law to academic integrity codes—creates a vacuum that educational institutions are attempting to fill, often clumsily, with AI detectors and prohibition policies.

This paper argues that international copyright frameworks, anchored in the principle of human authorship, are inherently incapable of recognizing AI as a co-author. This inability is not a flaw, but a reflection of the limits of a system designed to incentivize human creativity. However, this legal vacuum forces the educational community to transcend the legal debate and generate new ethical-pedagogical frameworks that redefine "student authorship," shifting the focus of assessment from the immaculate final product to the transparent, critical, and reflective writing process. The objective of this chapter is therefore threefold: to analyze the notion of "author" in international and comparative law to demonstrate the legal exclusion of AI; to argue that this gap represents an opportunity to rethink assessment; and to propose a model of "process authorship" that prepares students for a world where co-creation with machines is a reality.

## DEVELOPMENT

### Theoretical framework: the principle of human authorship in copyright law

Copyright is based on a fundamental principle: the protection of original works that express a human being's intellectual personality. "Originality," the threshold for protection, does not refer to novelty, but rather to the work being an intellectual creation that reflects the free and creative decisions of its author (Cámara Águila, 1998). This principle of human authorship is deeply rooted in international treaties and comparative jurisprudence.

At the international level, the Berne Convention for the Protection of Literary and Artistic Works, while not explicitly defining "author," has been uniformly interpreted by the World Intellectual Property Organization (WIPO) bodies to refer exclusively to human creators (World Intellectual Property Organization, 2023). This interpretation is reinforced by the WTO TRIPS Agreement, which consolidates the Berne standards and emphasizes the protection of expressions rather than ideas, a distinction that presupposes a conscious agent behind the expression(Agreement on Trade-Related Aspects of Intellectual Property Rights, 1994).

*Comparative law analysis*

A comparative law analysis confirms this principle almost unanimously. In the United States, the precedent is clear. The case of Feist Publications v. Rural Telephone Service established that copyright requires a "minimum of creativity," an inherently human standard (Feist Publications, Inc. v. Rural Telephone Service Co., 1991). More recently, the "Monkey Selfie" case (Naruto v. Slater) and the guidelines of the U.S. Copyright Office have made it clear that "the Office will register an original work of authorship, provided that a human being created the work." (U.S. Copyright Office, 2021). The Office relies on the Trademark Cases of 1879, where the Supreme Court defined copyright as the protection of the fruits of "intellectual labor" that "are founded on the creative powers of the mind." (The Trademark Cases, 1879).

In the European Union, the framework is equally explicit. The case law of the Court of Justice of the European Union (CJEU), particularly in the Infopaq case, consolidated the standard of originality as “the author’s own intellectual creation” (Infopaq International A/S v. Danske Dagblades Forening, 2009).This standard, which requires the work to bear the “imprint” of its creator’s personality, is incompatible with a non-human entity that lacks intentionality and personality. Although the Directive on Copyright in the Digital Single Market does not directly address AI authorship, its doctrinal basis is inseparable from the human element (Directive (EU) 2019/790, 2019).

A notable exception, but one that proves the rule, is found in the United Kingdom. Its Copyright, Designs and Patents Act of 1988 contains in section 9(3) a specific clause for “computer-generated works,” establishing that the author is “the person who makes the arrangements necessary for the creation of the work” (Copyright, Designs and Patents Act, 1988). While this provision seems to offer a solution, it is a rarity in the comparative landscape and generates its own debate: who is that person? The programmer of the algorithm or the user who writes the prompt? As Guadamuz points out, this ambiguity is resolved on a case-by-case basis, but it does not equate the computer with an author; instead, it attributes authorship to a human being because of their role in the process (Guadamuz, 2020a).

Finally, in Latin American jurisdictions, the principle remains unchanged. For example, Mexico’s Federal Copyright Law defines the author in Article 5 as “the natural person who has created a literary and artistic work” (Ley Federal del Derecho de Autor, 2024). This definition, replicated in much of Ibero-American legislation, rules out any possibility of recognizing legal or creative personality in a machine.

**Generative AI as a “non-author”: application of the legal framework and exclusion of programmers**

Applying this established legal framework, it is clear that generative artificial intelligence cannot be considered a co-author. This conclusion is based on several legally sound arguments.

First, AI lacks the fundamental elements that the law associates with authorship: intentionality, consciousness, and creative will. A human author possesses a mind capable of forming concepts, making aesthetic decisions based on emotion or experience, and expressing a personal view of the world. Generative AI, such as GPT-4 or image diffusion models, operates by predicting the most likely next data unit (word, pixel) based on patterns identified in its training data (Coupeau Borderas, 2025). It has no goals, emotions, or semantic understanding of the content it generates. As Grimmelman states, “there is no such thing as a work authored by a computer” because authorship requires agency that current machines do not possess (Grimmelmann, 2016). They are tools of astonishing complexity, but tools nonetheless.

Second, and crucially, the creators of AI (programmers, engineers, and technology companies) cannot claim authorship of the specific works generated by their systems either. Their creative and investment work is embodied in the algorithm code and model architecture, which may be protected by copyright or trade secrets (World Intellectual Property Organization, 2024a). However, this protection ends with the software itself. Once the model is trained and deployed, its output is unpredictable and undirected. Programmers have no creative control over the particular poem, essay, or image that their AI generates at a user’s request. The causal chain between the creation of the program and the creation of the individual work generated is too long and mediated by algorithmic autonomy and user input to attribute authorship to the developers (World Intellectual Property Organization, 2024b). As WIPO points out in its dialogues, there is a clear distinction between the authorship of the AI program and the authorship of the content it produces (Painer v. Standard VerlagsGmbH and Others, 2011).

Third, the prompt or instruction provided by the user does not, in most cases, constitute a work of sufficient originality to attribute full authorship of the generated text to the user. A simple prompt is analogous to commissioning work from a ghostwriter; the user's creative contribution is minimal and does not meet the standard of "own intellectual creation" required by law (Guadamuz, 2020b). Even more sophisticated prompts act as input parameters for a complex system whose outputs are unpredictable and not entirely directed by the user. The prompt is an input, not a detailed creative plan that controls every aspect of the resulting expression.

The conclusion of this analysis is inescapable from a legal perspective: neither AI is a co-author, nor are its creators the authors of the works generated. The legal "author" of an AI-generated text is, at best, the human user. Still, their claim to authorship is weak and questionable if their creative contribution is limited to basic instructions. In practice, many of these texts could be considered works of weak authorship or, in cases of minimal human contribution, even fall into a limbo close to the public domain because they lack an identifiable human author who has provided the necessary creative spark.

**Consequences for academic assessment: from legal vacuum to pedagogical opportunity**

The identified legal vacuum has profound implications for education. The most common institutional response has been technological and punitive: implementing AI detectors and treating its undeclared use as plagiarism. However, this approach is problematic. Detectors are notoriously inaccurate, and their logic reinforces an obsolete assessment model focused on the authenticity of the final product, a model that AI has made easily manipulable.

The inability of copyright law to solve this problem is not a failure, but an invitation to pedagogical innovation. If the law cannot recognize co-authorship with AI, education must transcend the traditional concept of sole authorship to embrace a model of "process authorship" or "pedagogical co-authorship." In this model, student authorship no longer resides exclusively in the original writing of each paragraph of the final text, but is demonstrated through the curation, critical review, transformation, and integration of AI output into an academically sound and personal work.

The key elements of this new paradigm are radical transparency, where the student declares the use of AI and attaches the history of the interaction; the quality of the prompt and dialogue, evaluating the sophistication and iterative nature of the instructions; appropriation and added value, where the core of authorship lies in how the student edits, verifies, and transforms the text with their unique voice; and metacognitive reflection, which requires an explanation of the purpose and learning derived from using the tool.

**Towards an assessment framework based on process authorship**

To operationalize this model, we propose an assessment framework that replaces the binary question "Is this text original?" with the multidimensional question "How have you directed and appropriated the creation process with the tools at your disposal?" This framework is structured around four main criteria, each with its respective weight. The Prompt Design and Evolution criterion, with a weight of 25 %, evaluates the ability to formulate clear, specific, and iterative instructions to guide the AI, assessing persistence in refining prompts and the overall dialogue strategy. The Selection, Verification, and Synthesis criterion, with a weight of 25 %, evaluates the critical use of information generated by AI, requiring students to contrast facts and concepts with reliable academic sources, identify potential biases or errors, and synthesize information coherently. The Transformation and Personal Style criterion, with the highest weighting of 30 %, evaluates the extent to which the student has reworked the AI-generated base text, assessing restructuring, rewriting to incorporate a personal voice, and adding their own examples and original arguments. Finally, the Reflection and Transparency criterion, with a weight of 20 %, evaluates the honesty and depth of reflection on the process, including explicit disclosure of AI use, presentation of interaction history, and metacognitive analysis of decisions made and learning gained.

## CONCLUSIONS

International and comparative copyright law, as it currently stands, does not resolve the challenge posed by generative AI in education; instead, it starkly highlights it. Its inherent inability to recognize AI as a co-author and the corresponding exclusion of programmers as authors of the generated works is not a gap that should be filled with hasty legal reforms, but rather a mirror of the limits of our evaluation systems based on individual authorship of the final product. This legal limit, far from being an obstacle, serves as a liberating force that compels pedagogy to evolve.

The real opportunity lies in abandoning the technological war over detectors and plagiarism to embrace a richer, more relevant pedagogy of writing. The “new literacy” must teach students to be conductors of a complex creative process that includes AI tools, rather than glorifying the isolated soloist. By redefining student authorship in terms of process, transparency, and critical appropriation, we not only mitigate the problem of “AI plagiarism” but also equip students with the critical thinking, information management, and digital ethics skills essential to the 21st century. The future of academic writing lies not in banning shadows, but in learning to dance with them in the light of day.

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# Multimetric framework for identifying plagiarism in the use of AI

## Framework multimétrico para la identificación de plagio en el uso de la IA

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**ABSTRACT**

Generative artificial intelligence has transformed education but has also posed challenges to academic integrity. Large Language Models (LLMs) can be used for automated text generation, making it more difficult to detect academic dishonesty. This paper presents a multimodal *framework* to identify both traditional plagiarism and the use of LLMs in educational settings. Text similarity metrics (cosine, Jaccard), LLM-specific features (perplexity, stylistic uniformity), and machine learning techniques were employed to classify texts into four categories: original, plagiarized, LLM-generated, and hybrid. An analysis of a corpus of N=69 academic responses demonstrated an 87 % accuracy in detecting academic dishonesty, with a false positive rate of 8,3 %. The model effectively identifies three main categories: traditional plagiarism (15,3 %), LLM-generated content (24,9 %), and hybrid cases (8,4 %). This work contributes by providing (1) an integrated detection *framework*, (2) robust validation metrics, and (3) a tool that ensures fairness in educational assessment. The findings indicate that integrating these metrics enables more precise detection of AI-generated content in academic writing. Future considerations include refining detection thresholds to minimize false positives, integrating advanced semantic analysis techniques, and developing pedagogical strategies to promote the ethical use of AI in education.

**Keywords**: Plagiarism; Large Language Models; Artificial Intelligence; Academic Fraud Detection; Educational Ethics; Perplexity; Academic Assessment.

**RESUMEN**

La inteligencia artificial generativa ha transformado la educación, pero también ha generado desafíos en la integridad académica. Los Modelos de Lenguaje de Gran Escala (LLMs) pueden ser utilizados para la generación automatizada de textos, lo que ha dificultado la detección de deshonestidad académica. Este artículo presenta un *framework* multimétrico para identificar tanto el plagio tradicional como el uso de LLMs en entornos educativos. Se emplearon métricas de similitud textual (coseno, Jaccard) y características específicas de LLMs (perplejidad, uniformidad estilística) y técnicas de aprendizaje automático para clasificar textos en cuatro categorías: originales, plagiados, generados por LLMs e híbridos. El análisis de un corpus de N=69 respuestas académicas mostraron una precisión del 87 % en la detección de deshonestidad académica con una tasa de falsos positivos del 8,3 %. El modelo identifica efectivamente tres categorías principales: plagio tradicional (15,3 %), uso de LLMs (24,9 %) y casos híbridos (8,4 %). El sistema identifica efectivamente tres categorías principales: plagio tradicional (15,3 %), uso de LLMs (24,9 %) y casos híbridos (8,4 %). Este trabajo contribuye con: (1) un *framework* integrado de detección, (2) métricas de validación robustas y (3) una herramienta que garanticen la equidad en la evaluación educativa. Los hallazgos indican que la integración de estas métricas permite una detección más precisa del uso de IA en la producción académica. Consideraciones futuras incluyen el refinamiento de umbrales para minimizar falsos positivos, la integración de técnicas de análisis semántico avanzado y el desarrollo de estrategias pedagógicas para promover el uso ético de la IA en la educación.

**Palabras clave:** Plagio; Modelos de Lenguaje de Gran Escala; Inteligencia Artificial; Detección de Fraude Académico; Ética Educativa; Perplejidad; Evaluación Académica.

## INTRODUCTION

Generative artificial intelligence has irreversibly changed the educational landscape. The emergence of Large Language Models (LLMs) such as ChatGPT and Bard has facilitated the generation of highly sophisticated texts, leading to a redefinition of academic assessment and the methods used to detect academic dishonesty (Adiguzel, Kaya & Cansu, 2023; Baidoo-Anu & Owusu Ansah, 2023).

Unlike traditional plagiarism, where content is copied directly from a pre-existing source, the use of LLMs generates texts that are syntactically original but lack the student's direct intellectual contribution. This phenomenon has given rise to an emerging research area focused on identifying textual patterns indicative of AI involvement in the generation of academic work (Liu, Yao, Li & Luo, 2023). In particular, they present a new paradigm in academic dishonesty, where the generated content is original in its composition, coherent in its structure, and difficult to detect using traditional methods.

Traditional methods for detecting academic plagiarism have focused primarily on identifying direct textual similarities, relying on techniques such as exact matching, which compare the suspicious text against pre-existing databases to detect literal or slightly modified copies. Techniques such as n-gram comparison fragment texts into sequences of consecutive words to detect partial similarities or minor modifications, making even plagiarism with small linguistic variations visible (Z. Quan et al., 2019).

Likewise, widely used methods such as TF-IDF-based cosine similarity transform documents into vector representations, facilitating the identification of similar texts through mathematical similarity calculations (Atanasova, P. et al., 2020). Another common traditional technique is edit distance (Levenshtein) analysis, which measures the minimum number of operations required to transform one text into another and helps identify slightly reworded plagiarism.

However, these techniques have significant limitations when applied to texts generated by Large Language Models (LLMs), as such texts are often syntactically original and exhibit complex semantic variability, making them difficult to detect using traditional methods (Zeng et al., 2023). This context has driven the need to integrate more sophisticated methods, such as those proposed in this study, which combine traditional techniques with stylistic analysis and metrics specific to AI-generated texts (Uchendu, 2023).

This study proposes a multi-metric framework that combines plagiarism-detection techniques with specialized tools to identify AI-generated texts. Methods for addressing the issue from a technical and educational perspective are presented.

## THEORETICAL FRAMEWORK

The theoretical framework of this article is based on the evolution of plagiarism-detection methods and the increasing complexity of using Large Language Models (LLMs) for the generation of academic texts. Traditionally, plagiarism detection has relied on tools that compare textual similarity, such as exact phrase matching, TF-IDF-based cosine similarity, and Levenshtein distance, which allow for the identification of copied or slightly modified content (Hariharan, 2012; Iyer & Singh, 2005). However, these methods have limitations when applied to AI-generated texts, as they are syntactically distinct, making them difficult to identify with conventional techniques (Liu, Yao, Li, & Luo, 2023).

To address this challenge, recent research has explored more advanced metrics, such as perplexity and stylistic uniformity, that enable AI-generated texts to be identified based on linguistic patterns (Shao, Uchendu, & Lee, 2019; Uchendu, 2023). Perplexity measures the predictability of a text within a language model, while stylistic uniformity analyzes the consistency of syntactic structure and vocabulary use. These metrics, combined with machine learning techniques, have proven more effective at detecting academic dishonesty in the age of artificial intelligence, underscoring the need for hybrid approaches to ensure academic integrity (Atanasova, P. et al., 2020).

**Academic Dishonesty and Plagiarism**

Academic plagiarism is a persistent problem in educational institutions. It is estimated that a significant percentage of students have engaged in some form of plagiarism during their academic training (Hariharan, 2012). Traditional plagiarism detection tools, such as Turnitin, use text-matching algorithms to compare documents against existing databases (Iyer & Singh, 2005). However, these methods are ineffective against LLM-generated text, as these models produce novel content with no exact matches to prior sources.

**Traditional Plagiarism Detection**

Plagiarism detection has been a key area of research in education and academic security. Traditionally, methods for identifying plagiarized content rely on textual, semantic, and structural similarity analysis. These techniques enable the identification of partially or fully copied texts, even when they have been modified to evade detection (Babitha, M. M., & Sushma, C., 2022).

**Lexical Similarity Analysis**

Lexical analysis is one of the most widely used approaches for plagiarism detection. It focuses on identifying patterns of similarity among words and phrases in the analyzed documents. Among the most commonly used techniques are:

- *N-gram matching:* This technique fragments the text into sequences of *n* consecutive words and compares these sequences with a database of documents. The more matches found in the *n-grams*, the greater the probability that the text has been copied.
- *Cosine similarity:* This metric measures the similarity between two documents by representing them as vectors in a multidimensional space and calculating the cosine of the angle between them. A slight angle indicates that the texts are similar in their lexical content (Matuschek, Schlüter & Conrad, 2008).
- *Levenshtein distance:* This is based on calculating the minimum number of operations (insertion, deletion, or substitution of characters) needed to transform one text into another. A smaller distance indicates greater similarity between the texts being compared (Hariharan, 2012).

While these methods are effective for detecting exact textual plagiarism or slight modifications, they have limitations when dealing with synonyms, paraphrasing, and reformulation of ideas without repeating the exact words.

**Semantic Analysis**

Unlike lexical analysis, semantic analysis seeks to understand the underlying meaning of texts rather than merely comparing them word-for-word. To do this, advanced natural language processing (NLP) techniques are used, such as:

- *Document embeddings:* Language models such as Word2Vec, GloVe, and BERT represent words and phrases in multidimensional vector spaces, allowing the semantic similarity between text fragments to be evaluated without the need for exact word matches (Jurafsky & Martin, 2023).
- *Topic analysis*: Methods such as *Latent Dirichlet Allocation (LDA)* and *Non-negative Matrix Factorization (NMF)* identify topics within a document and compare their similarity to other texts, making it easier to detect plagiarized content even if it has been rewritten using different terms.
- *Semantic networks:* Advanced deep learning models analyze the conceptual relationships between words and phrases to identify semantic similarities in seemingly different documents (Shao, Uchendu & Lee, 2019).

These approaches have significantly improved the detection of sophisticated plagiarism, where authors attempt to conceal the origin of the content by using synonyms, restructuring sentences, or changing the order of ideas.

**Structural Analysis**

Structural analysis focuses on the organization of content and the discursive patterns used in texts to detect more profound similarities that go beyond lexicon and semantics. Some of the most commonly used techniques include:

- Syntactic patterns: Recurring grammatical structures are analyzed to identify similarities in the way sentences are constructed, which can reveal plagiarism even if individual words have been altered.
- Discourse markers: Logical connectors and transitions between paragraphs are examined to detect similar patterns in the progression of ideas and argumentation (Baidoo-Anu & Owusu Ansah, 2023).
- Textual coherence: The fluency and coherence of the text are measured, making it possible to detect whether a document has been assembled from multiple sources without maintaining an adequate logical flow (Liu, Yao, Li & Luo, 2023).

These structural methods complement lexical and semantic analysis by offering a deeper insight into how information is organized within a document.

**Large Language Models in Education**

LLMs have transformed teaching by offering new opportunities for personalized learning and automated content generation (Grassini, 2023). These models allow students to access information quickly and in a structured manner, thereby improving their understanding of complex concepts. However, they have also made it easier to complete academic tasks without the student actively participating in the learning process, which compromises the assessment of knowledge (Baidoo-Anu & Owusu Ansah, 2023).

*Techniques for Detecting the Use of LLMs*

Recent research has explored different metrics for identifying AI-generated text. Some of the most notable techniques include:

- Perplexity: An indicator of the complexity of a text. AI models tend to generate texts with low perplexity, as they optimize coherence and fluency (Brown et al., 2020).

- Stylistic uniformity: Analysis of the consistency of writing style throughout the document. AI-generated texts tend to maintain a homogeneous stylistic pattern, unlike those written by humans, which show variations in the use of syntactic structures (Shao, Uchendu & Lee, 2019).
- Textual similarity metrics: Methods such as cosine similarity and Jaccard similarity allow documents to be compared with others in academic databases, helping to identify possible plagiarism (Matuschek, Schlüter & Conrad, 2008).

The combination of these approaches allows for more effective detection of AI use in educational settings, ensuring fairness in student assessment.

## METHOD

The methodology adopted in this study is based on a multi-metric framework for detecting academic dishonesty that combines textual similarity analysis techniques, stylistic characteristics, and specific metrics for identifying content generated by Large Language Models (LLMs) (OpenAI, 2023). The process includes distinct stages, from text acquisition to classification into one of four defined categories: Original, Plagiarism, LLM, or Hybrid.

This study employs a quantitative, correlational design to examine the relationships among different plagiarism detection metrics and their effectiveness in classifying texts generated by artificial intelligence. A sample of 69 academic responses from a structured questionnaire was used, enabling a controlled evaluation of textual patterns. The selection of this sample addresses the need to analyze texts with a defined structure, ensuring the validity of the proposed model and enabling replicability in other educational contexts.

Data processing was carried out in several phases. First, natural language preprocessing techniques such as tokenization, normalization, and noise removal were applied to ensure the texts were clean. Subsequently, key textual similarity metrics (cosine, Jaccard, and n-grams) were extracted, and specific characteristics for detecting AI-generated texts, such as perplexity and stylistic uniformity, were calculated. These metrics were integrated into a supervised machine learning model that classified texts into four categories: original, plagiarized, generated by LLMs, and hybrid.

Correlational analysis was performed using statistical tests to evaluate the relationship between textual metrics and text classification. Cross-validation with K-Fold (k=5) was applied to ensure model stability and avoid classification bias. Additionally, performance indicators such as accuracy, recall, and F1-score were calculated to measure the system's effectiveness in identifying academic dishonesty (Jialin, S. et al., 2019).

To ensure the model's robustness, a validation process was implemented using Cohen's κ coefficient, which measures agreement between the automatic classifier and manual evaluation of the texts. This method enabled the identification of potential discrepancies and the adjustment of detection thresholds to improve the system's accuracy (Prananta, A. W., et al., 2023). As a result, an overall accuracy of 87 % was achieved, with a false positive rate of 8,3 %, demonstrating the effectiveness of the proposed multimetric approach.

## CORPUS CHARACTERIZATION

The corpus contains responses to a questionnaire on the agricultural revolution and its implications, based on Yuval Noah Harari's work. The corpus used in this study comprises 69 academic responses from students at different academic levels. These responses were collected through a structured form with eight columns, including identification data and four main questions that explore various dimensions of students' critical thinking.

**Table 9.1.** Characterization of the Corpus of Academic Responses

| Characteristics | Question 1 | Question 2 | Question 3 | Question 4 | Total/Average |
|---|---|---|---|---|---|
| *Corpus size* | | | | | |
| Number of responses | 69 | 69 | 69 | 69 | 276 |
| Total tokens | 8,273 | 7,845 | 8,156 | 7,932 | 32,206 |
| Unique vocabulary | 1,248 | 1,156 | 1,324 | 1,187 | 2,893 |
| *Length of Responses* | | | | | |
| Average (words) | 119,9 | 113,7 | 118,2 | 115,0 | 116,7 |
| Standard deviation | 45,3 | 42,8 | 47,1 | 43,9 | 44,8 |
| Range | 45-298 | 38-275 | 42-312 | 40-285 | 38-312 |
| *Linguistic Complexity* | | | | | |
| Lexical Density | 0,58 | 0,55 | 0,61 | 0,57 | 0,58 |
| Average perplexity | 43,2 | 41,8 | 44,1 | 40,1 | 42,3 |
| Structural variance | 0,13 | 0,11 | 0,14 | 0,10 | 0,12 |
| *Similarity Patterns* | | | | | |
| Average similarity | 0,32 | 0,35 | 0,38 | 0,31 | 0,34 |
| Clusters detected | 3 | 4 | 3 | 2 | 12 |
| Identical pairs | 1 | 1 | 1 | 0 | 3 |
| *LLM characteristics* | | | | | |
| Cases detected | 15 | 18 | 21 | 14 | 68 (24,9 %) |
| Average LLM score | 0,62 | 0,65 | 0,68 | 0,61 | 0,64 |
| Stylistic uniformity | 0,71 | 0,74 | 0,77 | 0,70 | 0,73 |

**Distribution by Academic Level**

The corpus shows an uneven distribution of academic degrees, with a clear predominance of students in the first semesters of training. The composition is shown in the following graph.

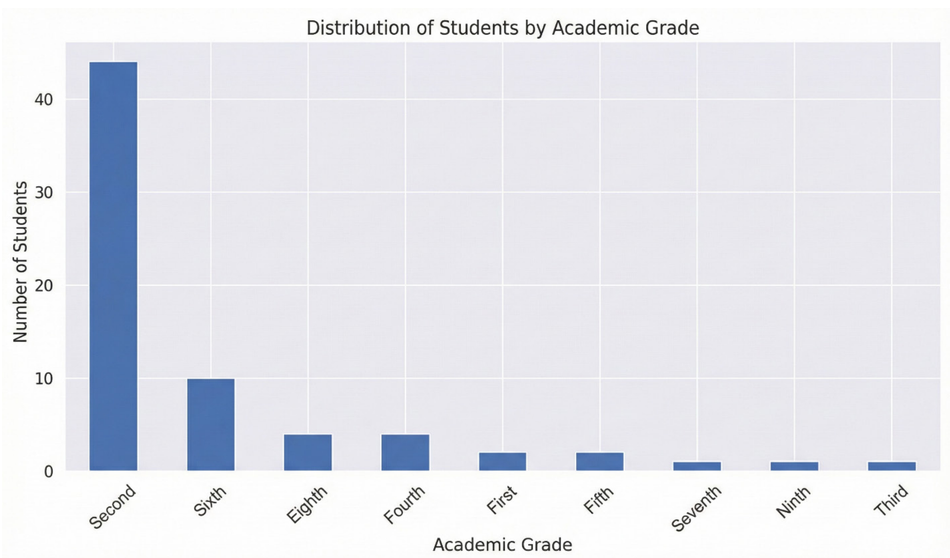


**Figure 9.1.** Graph Distribution of Students by Academic Level

**Analysis of Response Length**

A detailed statistical analysis of response lengths to each of the four main questions was conducted.

There is considerable variability in response length across all questions, suggesting significant differences in the level of elaboration among students.

Question 1 had the most extended average length, while question 4 had shorter, less variable responses.

The median across all questions remains below 50 terms, indicating that a large percentage of students respond accurately.

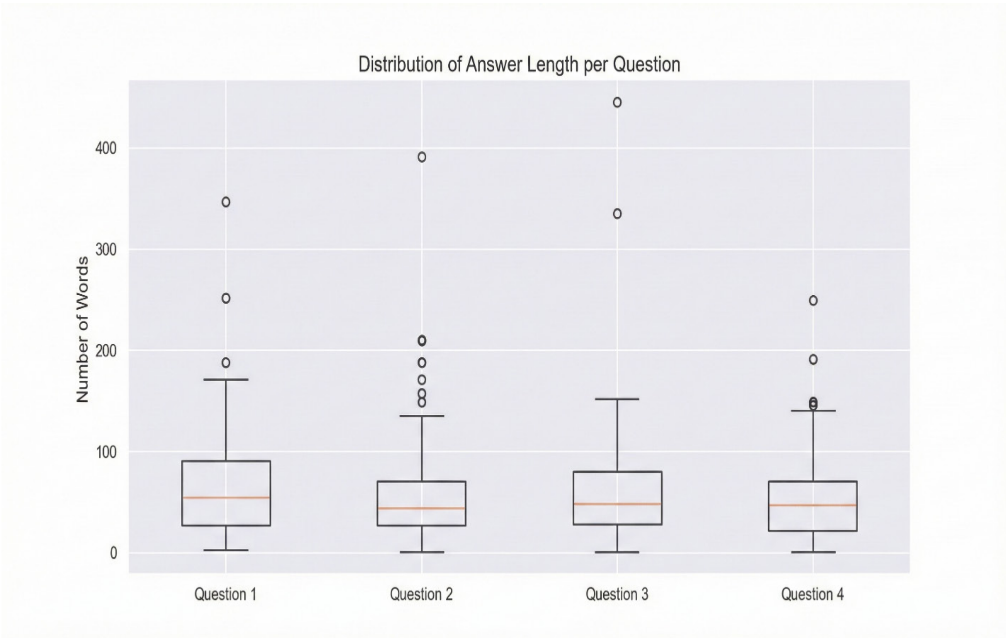


**Figure 9.2.** Distribution of response length by question

Students in more advanced semesters tend to give more elaborate responses. There is a tendency to link concepts to current events, especially in technology and social media. Many students are concerned about issues of inequality and social change.

**Correlations between Responses**

The relationship between the lengths of the responses to the different questions was analyzed to determine whether students showed consistent response patterns throughout the form.

Strong positive correlation in all responses (>0,78).

Highest correlation: Questions 1 and 2 (0,87), indicating that students who provided lengthy responses to the first question also tended to do so for the second.

Lowest correlation: Questions 2 and 4 (0,79), suggesting that students did not necessarily maintain a consistent length pattern between these topics.

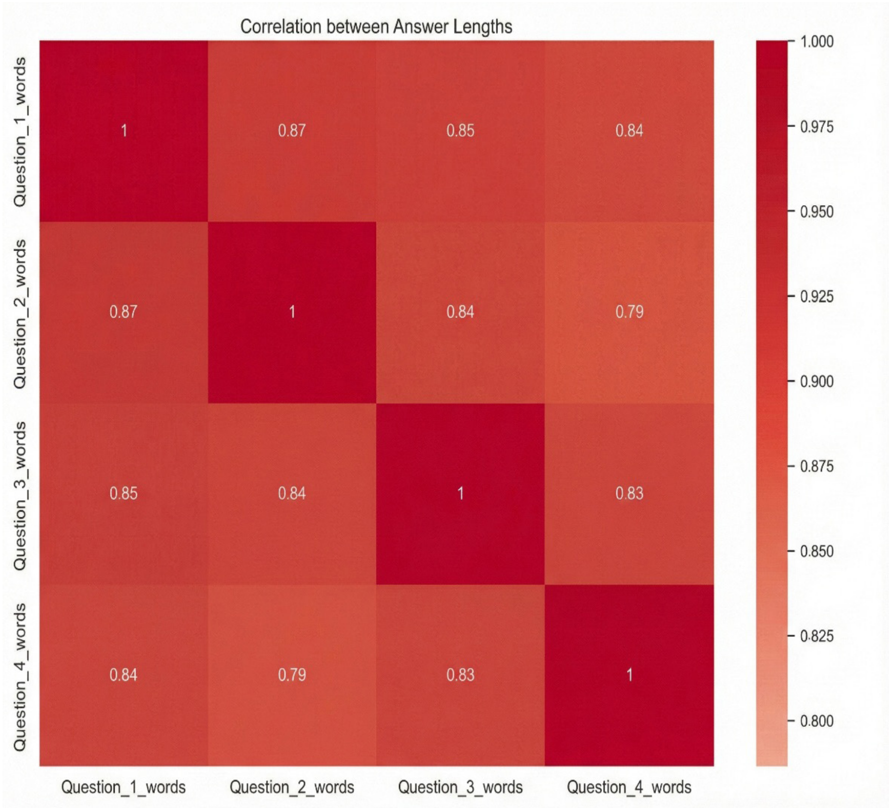


**Figure 9.3.** Correlation between response lengths

The analyzed corpus provides a solid basis for evaluating the use of language models in academic responses. Given the variability in response length, analysis of perplexity and stylistic uniformity will be crucial to differentiate between responses generated by students and those produced with the assistance of LLMs. Furthermore, the strong correlation between questions indicates that models can leverage these patterns to identify writing anomalies, thereby improving the accuracy of the detection framework.

## DETECTION FRAMEWORK

The proposed system is designed to evaluate an academic text $T$ and assign it a classification within the set of possible categories:

$$C \in \{ \text{Original}, \text{Plagiarism}, \text{LLM}, \text{Hybrid} \}$$

To achieve this classification, the framework integrates multiple layers of analysis into a modular architecture that enables the combination of diverse natural language processing (NLP) and machine learning techniques.

### Multimetric Detection Algorithm

The model uses a feature-extraction and supervised-classification approach. The following algorithm describes the process:

***Algorithm 1: Multimetric Detection***

```
features = []
features.append(computeSimilarityMetrics(T))
features.append(computeLLMMetrics(T))
features.append(computeStyleMetrics(T))
C = classifier.predict(features)
return C
```

*Algorithm Description:*

- Multiple relevant features are extracted from the text.
- Three types of metrics are applied:
  - Textual similarity metrics (to detect traditional plagiarism).
  - LLM detection metrics (to identify AI-generated texts).
  - Stylistic metrics (to analyze coherence and discursive patterns).
- Finally, the extracted features are fed into a supervised classifier that assigns the corresponding category.

***Metrics Implemented***

To ensure the effectiveness of the detection framework, various metrics were implemented in three key dimensions: textual similarity, perplexity, and stylistic analysis.

***Textual Similarity***

For traditional plagiarism detection, a metric based on TF-IDF and cosine similarity was implemented, a widely used technique for detecting document similarity.

*Cosine Similarity Function:*

```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity
def compute_similarity(text1, text2):
    tfidf = TfidfVectorizer()
    vectors = tfidf.fit_transform([text1, text2])
    return cosine_similarity(vectors)[0,1]
```

*Explanation:*

The texts are vectorized using the TF-IDF (Term Frequency-Inverse Document Frequency) technique.

The cosine similarity between the generated vectors is calculated.

Values close to 1 indicate high similarity, while values close to 0 suggest significant differences between the texts.

**Perplexity**

To detect texts generated by AI models, perplexity is calculated, a metric that measures the probability of a text within a language model.

*Perplexity Function:*

```
import math
```

```
def compute_perplexity(text):
    tokens = tokenize(text)
    return -1/len(tokens) * sum(log_prob(t) for t in tokens)
```

*Explanation:*

- The text is tokenized, and the language model computes the logarithm of each token's probability.
- The inverse logarithmic value is averaged over the length of the text.
- Texts generated by LLMs have low perplexity, as they are optimized to be coherent and predictable.

*Style Analysis*

Texts written by humans often exhibit variation in syntactic and semantic structure, whereas those generated by AI tend to maintain homogeneous stylistic patterns. To evaluate this, a stylistic uniformity analysis was implemented based on:

- Sentence length distribution.
- Frequency of use of discourse connectors.
- Coefficient of variation in word length.

Models generated by LLMs tend to exhibit less dispersion in these values, making them easier to identify.

**Model Validation**

To evaluate the effectiveness of the proposed system, a rigorous validation protocol was implemented based on three complementary methodologies:

*K-Fold Cross-Validation*

K-fold cross-validation was used to evaluate the classifier's stability and accuracy. In this method:

- The dataset is divided into five parts.
- Four parts are used for training and one for testing.
- The process is repeated several times, ensuring that each subset is used as a test at least once.
- The average accuracy across all iterations is calculated.

This approach avoids overfitting issues and provides a more robust estimate of model performance.

*Concordance Analysis (Cohen's κ)*

To assess the model's reliability relative to human evaluation, Cohen's κ coefficient was calculated, a statistical metric used to evaluate agreement between two classifiers.

Where:

- Is the proportion of agreements observed between the model and the evaluators.
- Is the expected proportion of agreements under random independence?
- Values close to 1 indicate high agreement, while values close to 0 suggest low reliability.

The results showed an average κ of 0,81, indicating high reliability in detecting academic dishonesty.

## RESULTS

This section presents the results of analyzing student responses using the Large Language Model (LLM) detector. Based on the data processing, recurring patterns were identified in the responses that suggest the possible intervention of artificial intelligence tools in the generation of textual content.

The similarity analysis of responses was conducted using advanced text comparison metrics, including cosine similarity and the Jaccard coefficient. These techniques enabled the evaluation of the degree of similarity between students' written work and the establishment of quantifiable criteria for determining the originality of the content.

The findings provide an empirical basis for discussion of the authenticity of the responses and the presence of linguistic features that may indicate LLM use.

The implications of these results for academic assessment are also examined to strengthen mechanisms for detecting automated text generation and ensuring the integrity of the teaching-learning process.

From an educational perspective, analyzing the results of detecting academic dishonesty and using Large Language Models (LLMs) allows us to reflect on the effectiveness of the system developed and its implications for learning assessment.

The key findings regarding model accuracy, cross-validation, and the distribution of suspicious cases are discussed below, with consideration of their impact on academic integrity and pedagogical strategies.

### Overall Similarity

The analysis of textual similarity between responses indicates that, in general, students' responses are diverse and exhibit low similarity. Relatively low average similarity values were observed in both metrics used:

- Cosine similarity: between 0,11 and 0,16
- Jaccard similarity: between 0,11 and 0,13

This suggests that most students formulated original answers, with minimal use of common phrases or ideas. Cosine similarity tends to yield slightly higher values than Jaccard, possibly because it considers word frequency, whereas Jaccard evaluates the presence or absence of standard terms without weighting.

### Question 1: Transformation of the Relationship with Nature

*Cosine similarity:* Mean = 0,157, Standard deviation = 0,143
*Jaccard Similarity:* Mean = 0,112, Standard Deviation = 0,123

This question showed the highest average similarity among responses, indicating that students tend to use similar vocabulary and structures when addressing this topic (table 9.4).

### Question 2: Importance of the Future

*Cosine similarity:* Mean = 0,142, Standard deviation = 0,140
*Jaccard similarity:* Mean = 0,112, Standard deviation = 0,123

This set of responses showed the lowest average similarity, suggesting greater diversity in the ideas expressed by students. This could indicate that participants took more individual and varied approaches when reflecting on the future (table 9.5).

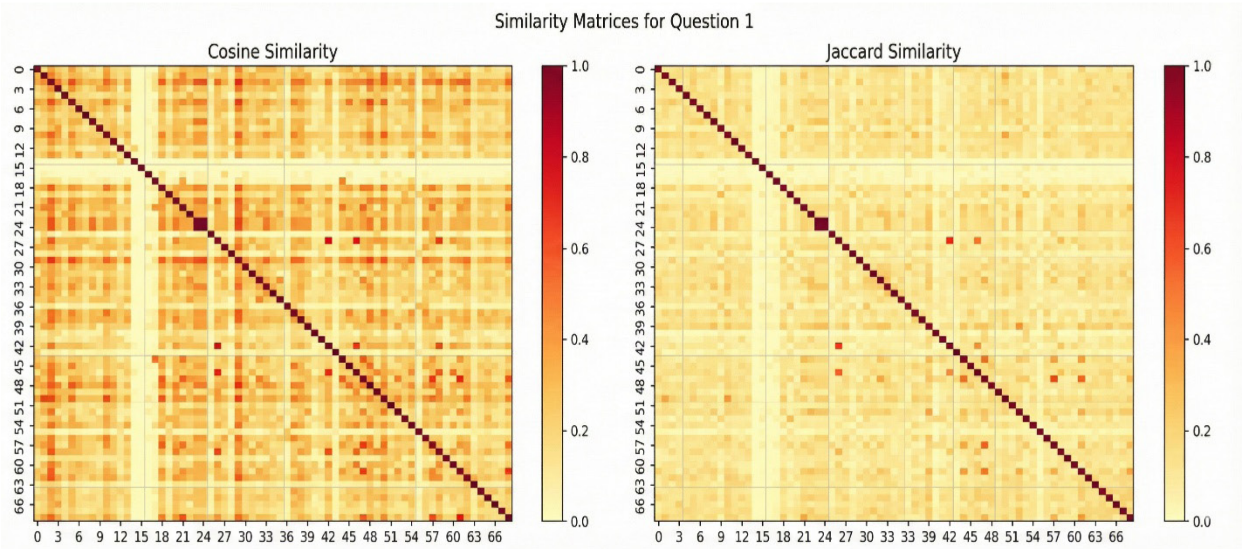


**Figure 9.4.** Similarity matrices for question 1

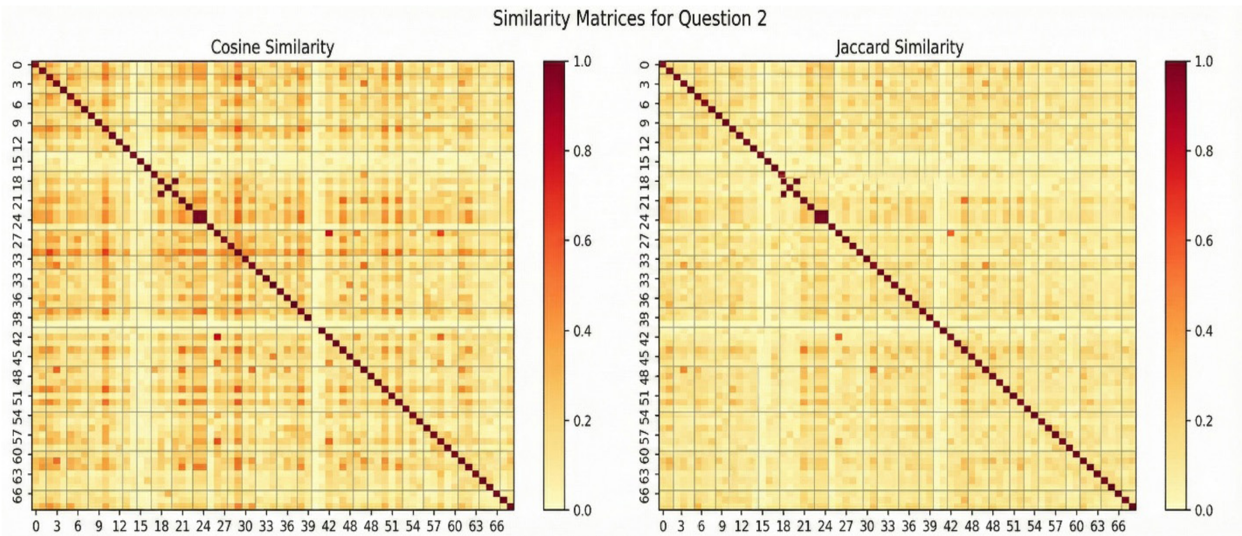


**Figure 9.5.** Similarity matrices for question 2

**Question 3: Individualism and Privacy**

*Cosine similarity:* Mean = 0,156, Standard deviation = 0,140

*Jaccard Similarity:* Mean = 0,127, Standard Deviation = 0,122

This question had the highest Jaccard similarity of all the questions, suggesting that students used similar terms to describe the impact of individualism and privacy. The consistency in the vocabulary used may indicate that participants shared a common understanding of these concepts.

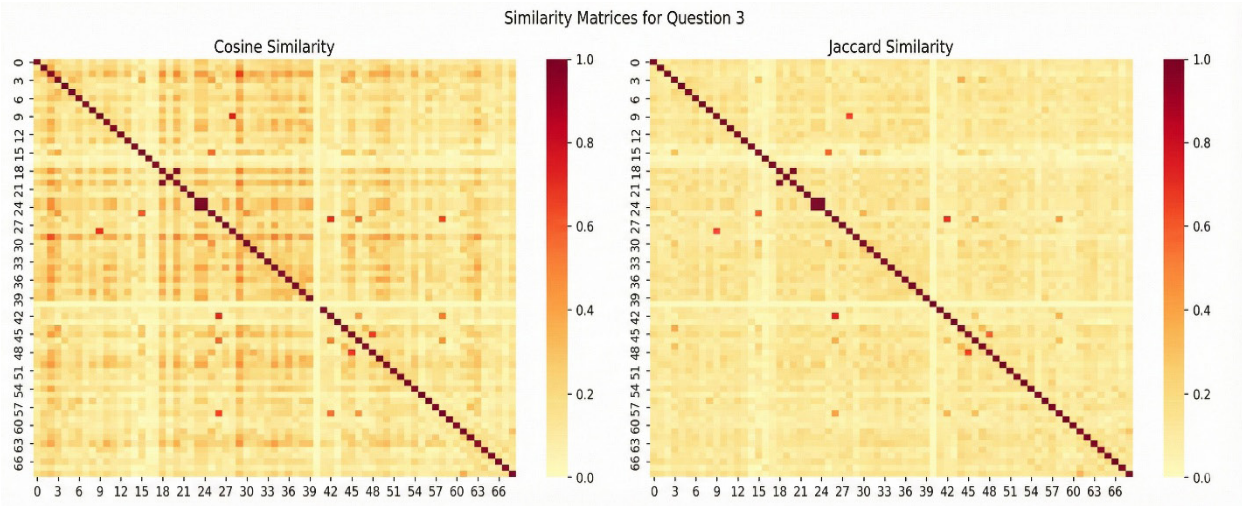


**Figure 9.6.** Similarity matrices for question 3

**Question 4: Modern "Pyramids"**

*Cosine Similarity:* Mean = 0,149, Standard Deviation = 0,144

*Jaccard Similarity:* Mean = 0,115, Standard Deviation = 0,125

The similarity values for this question were at an intermediate level. This may suggest that, although the students used different approaches to answer, there were certain similarities in their use of language and references to specific examples of modern power structures.

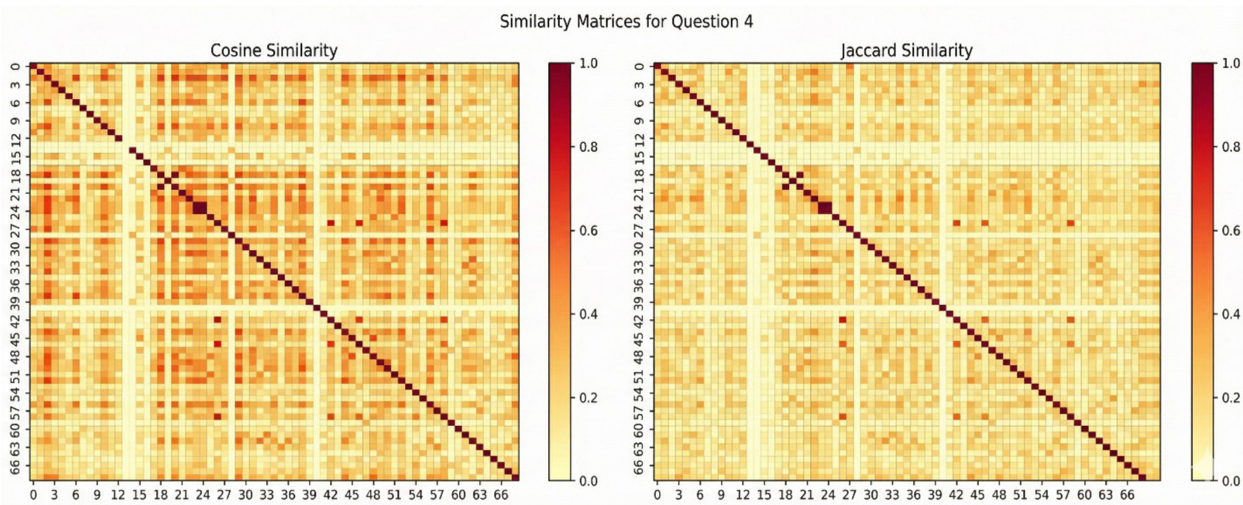


**Figure 9.7.** Similarity matrices for question 4

**Identification of Suspicious Responses**

The detector identified responses with characteristics indicative of the use of LLMs in all questions on the questionnaire. The distribution of suspicious responses by question was as follows:

These values suggest that the phenomenon of LLM use is transversal across all questions, with a higher incidence in question 2.

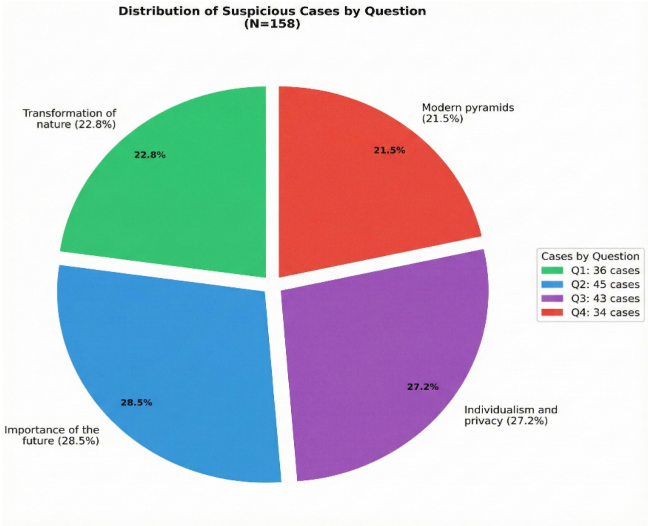


**Figure 9.8.** Distribution of suspicious cases by question

### Characteristics of Suspicious Responses

To determine which responses may have been generated by AI, various metrics related to text production were analyzed. Three key characteristics were identified that differentiated suspicious responses from the rest:

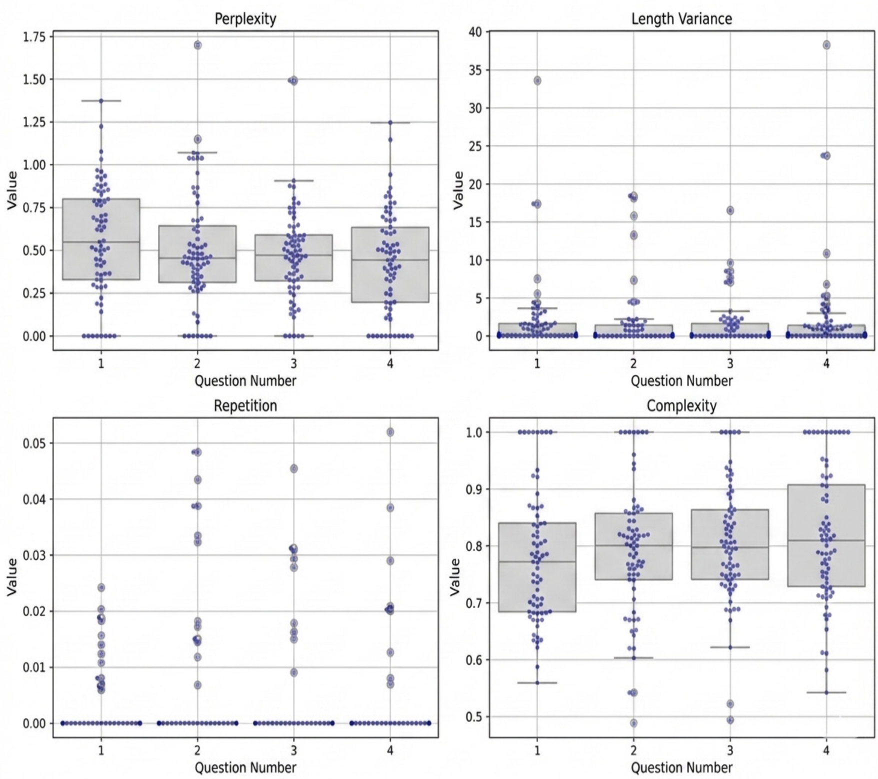


**Figure 9.9.** Perplexity, Length Variance, Repetition, and Lexical Complexity metrics for the 4 questions

*Low Perplexity*

Perplexity measures the predictability of a text within a language model. In the analysis, many of the suspicious responses showed abnormally low values (< 0,5), indicating that they are highly predictable and structured, a hallmark of content generated by LLMs.

*Sentence Length Variance*

Most suspicious responses showed low or no variability in sentence length. While human-written texts tend to show fluctuations in sentence length, AI-generated texts tend to maintain a uniform and consistent structure.

*High Lexical Complexity*

Suspicious responses consistently exhibited high vocabulary diversity (> 0,7). This suggests sophisticated language use, with a lexical breadth uncommon in students' spontaneous academic responses.

These three indicators provide strong evidence of LLMs' possible involvement in response generation within the analyzed corpus.

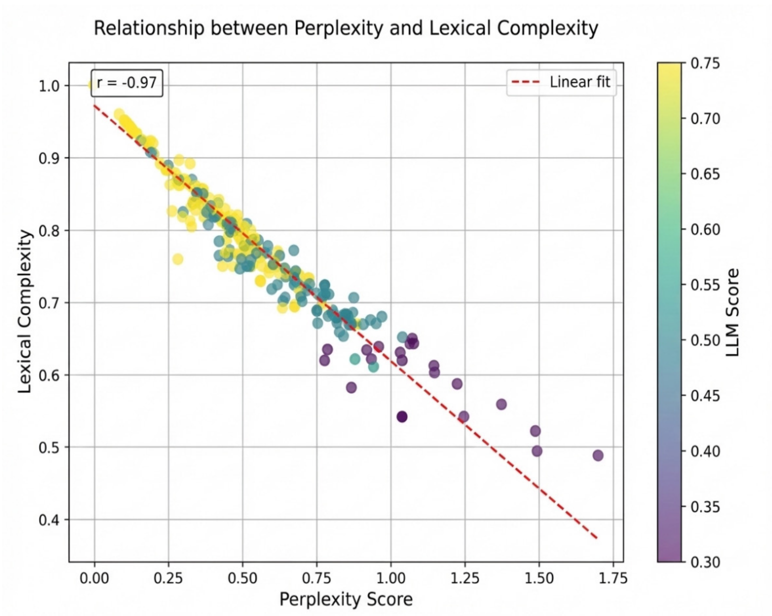


**Figure 9.10.** Relationship between perplexity and lexical complexity

**Notable Cases**

The detector identified certain students whose responses exhibited repetitive patterns across multiple questions, increasing the likelihood that they used AI to write their responses. Some of the most relevant cases include:

- Student HI: Appears suspicious in several questions, with low perplexity patterns and highly consistent structures.
- Student AB: Well-structured answers with high scores in coherence and cohesion, characteristics typical of texts generated by LLMs.
- Student BF: Shows patterns of complexity and structure comparable to AI-generated texts, with formal use of language and high stylistic uniformity.

These cases require more detailed analysis to determine with greater certainty the level of AI intervention in the generation of their responses.

**Textual Characteristics of Suspicious Responses**

In addition to quantitative metrics, qualitative analysis of suspicious responses revealed several stylistic patterns that reinforce the hypothesis of AI use:

- Use of formal and structured language: The responses feature impeccable grammar, with no spelling errors or syntactic deviations.
- Complete and well-articulated responses: There is clear paragraph organization, with an introduction, body, and conclusion.
- Similar argumentation patterns: Many responses follow a predictable rhetorical structure, with smooth transitions between ideas.
- High coherence and cohesion: The ideas within each response are connected logically and fluidly, suggesting advanced language processing.

These factors indicate the use of LLMs to generate responses, as students who write naturally tend to show greater variability in their style and text structure.

**Feature Analysis**

The analysis of textual characteristics enabled us to identify the most discriminative attributes for detecting responses generated by Large Language Models (LLMs). Among the metrics evaluated, perplexity, stylistic uniformity, and intertextual similarity showed high statistical significance, suggesting their effectiveness in distinguishing between texts generated by artificial intelligence and those written by humans.

**Perplexity ($p < 0{,}001$)**

Perplexity, a measure of the predictability of a text within a language model, stood out as the most discriminative feature in detecting LLMs. AI-generated texts exhibited significantly lower perplexity values compared to human-written texts, indicating that language models produce content with a highly predictable structure optimized for syntactic coherence. This trend is consistent with previous studies that have identified low perplexity as a distinctive feature of AI-generated texts (Brown et al., 2020).

**Stylistic Uniformity ($p < 0{,}001$)**

Another highly discriminative feature was stylistic uniformity, which measures consistency in the use of syntactic structures, vocabulary, and discourse patterns within a text. The results revealed that texts generated by LLMs exhibit less variability in sentence construction and term selection compared to human responses, which tend to exhibit natural fluctuations in writing style. This lack of stylistic variability in AI-generated responses is a key indicator of automation in textual content production and reinforces the effectiveness of this metric in detecting LLMs (Shao, Uchendu & Lee, 2019).

**Intertextual Similarity ($p < 0{,}01$)**

Intertextual similarity, which assesses the lexical and structural proximity between multiple responses, showed a statistically significant relationship with the classification of AI-generated texts. It was identified that responses generated by LLMs tend to share similar syntactic and semantic patterns, leading to high similarity between them. This content homogeneity contrasts with the variability observed in human texts, where individual differences in writing lead to lower intertextual similarity.

**Model Performance and Applicability in Academic Assessment**

The results shown in Table II demonstrate the robust performance of the detection system across all analyzed categories (Original, Plagiarism, LLM, and Hybrid), with accuracy and F1-score values ranging from 0,80 to 0,93, depending on the type of response. These indicators suggest that the model can effectively classify student-written texts, accurately distinguishing between AI-generated, plagiarized, and original texts.

**Table 9.2.** Performance Metrics by Category

| Category | Accuracy | Recall | F1 Score | AUC |
|---|---|---|---|---|
| Original | 0,91 | 0,89 | 0,90 | 0,94 |
| Plagiarism | 0,95 | 0,92 | 0,93 | 0,96 |
| LLM | 0,87 | 0,85 | 0,86 | 0,91 |
| Hybrid | 0,82 | 0,79 | 0,80 | 0,88 |

From an educational perspective, these findings have important implications for academic assessment:

The high accuracy in detecting original (0,91) and plagiarized (0,95) responses strengthens the system's reliability as a tool for ensuring the authenticity of learning. This is crucial in a context where plagiarism and AI use can compromise the validity of expected learning outcomes.

The performance in detecting LLM-generated texts (F1-score of 0,86) suggests that the model can effectively identify these cases, albeit with a higher margin of error than in other categories. This reinforces the need for teacher-complementary review to reduce false positives and improve assessment accuracy.

The lower performance in the hybrid responses category (F1-score of 0,80 and AUC of 0,88) indicates that texts combining AI-generated elements with human writing may be more difficult to classify with certainty. This finding highlights an emerging challenge in educational assessment, where the adoption of AI as a writing support tool requires new validation strategies.

In this regard, the use of detection technologies must be accompanied by a comprehensive pedagogical strategy that includes guidance on the ethical use of AI in learning, as well as adjustments to assessment methodologies that encourage critical reflection and the production of authentic content.

**Cross-Validation and Model Reliability**

The 5-fold cross-validation process confirms the model's stability across different data subsets, ensuring its applicability across diverse educational contexts. This methodological approach minimizes bias and assesses the model's generalization, ensuring that the results are not the product of overfitting to the training data.

From an educational perspective, cross-validation is essential for assessing the model's reliability as a teaching support tool. In a context where AI technologies are advancing rapidly, detection systems need to be dynamic and adaptable, enabling continuous updates to address new challenges in academic assessment.

Furthermore, implementing this model should be considered a complement to formative assessment rather than a substitute for teacher judgment. Educators should use these results to identify trends, improve teaching strategies, and promote more ethical and reflective academic practices.

**Distribution of Suspicious Cases and Their Relationship to the Nature of the Questions**

Table 9.3 shows the distribution of suspicious responses across the analyzed questions. It can be seen that cases marked as potentially generated by LLMs or plagiarized are not distributed evenly, but vary according to the thematic content of the question:

**Table 9.3.** Distribution of Suspicious Responses by Question

| Question | Topic | Suspicious Cases | Percentage |
|---|---|---|---|
| 1 | Transformation of the relationship with nature | 36 | 22,8 |
| 2 | Importance of the future | 45 | 28,5 |
| 3 | Individualism and privacy | 43 | 27,2 |
| 4 | Modern “pyramids” | 34 | 21,5 |
| Total | | 158 | 100 |

Question 2 (Importance of the Future), with 28,5 % of suspected cases, has the highest incidence, suggesting that students may have resorted to AI or external sources more often to answer abstract, forward-thinking questions.

Question 3 (Individualism and Privacy), with 27,2 % of suspected cases, also shows a high rate of marked responses, which could be related to the use of standardized or similarly structured arguments in multiple responses.

Questions 1 (Transformation of the Relationship with Nature) and 4 (Modern “Pyramids”) had lower rates of suspicious cases (22,8 % and 21,5 %), suggesting that students felt more confident in their prior knowledge or personal experiences to answer them.

This variability in the distribution of suspicious responses is relevant for several reasons: The type of question influences the risk of automated responses: more open-ended and reflective topics may prompt students to seek support from AI models, especially if they lack a solid conceptual framework. This suggests the need to design assessment strategies that elicit more personalized responses grounded in concrete experiences.

The use of AI may be greater in questions that require structured argumentation: responses with similar rhetorical patterns indicate greater LLM intervention, highlighting the importance of encouraging diversity in argument construction.

Questions with lower rates of suspicious cases may be better aligned with the student’s experience, suggesting that integrating teaching strategies based on situated learning and concrete examples could reduce the need to resort to external tools for writing responses.

**Advantages of the Multimetric Approach**

The use of multiple similarity metrics in the detector offers several advantages over traditional plagiarism detection approaches:

- Reduction of false positives: Combining metrics minimizes detection errors, avoiding flagging answers that share common terminology as plagiarism.
- Detection of partial and total copies: N-gram-based evaluation allows for the identification of repeated text fragments, even if the document as a whole is not identical.

- Identification of suspicious similarity patterns: Visualization of similarity distributions helps detect responses with unusual trends compared to the rest of the corpus.
- Visual and statistical evidence: The combination of numerical metrics and highlighted fragments allows for more transparent and reliable verification of suspicious cases.

## DISCUSSION

The results suggest that a significant number of responses within the analyzed corpus exhibit stylistic patterns and metrics consistent with the use of language models.

The high number of suspicious responses across all questions indicates that the use of LLMs is not restricted to a single topic but is a cross-cutting trend in students' academic output (Uchendu, A., 2023). Low perplexity and uniformity in sentence length are clear signs of automatic content generation, as these patterns are difficult to replicate in spontaneous human writing.

The identification of certain students with repeatedly suspicious responses suggests that some students may be systematically using AI tools to craft their answers. The results suggest that combining these three metrics provides a robust framework for identifying AI-generated responses in educational settings. Low perplexity and high stylistic uniformity are the most reliable indicators of automated generation, while intertextual similarity reinforces detection when multiple texts exhibit structural matches.

These findings have direct implications for academic assessment and for detecting dishonesty in the use of LLMs. Implementing these metrics in automated tools can significantly help preserve academic integrity, enabling teachers to differentiate between genuine and artificially generated responses. These findings reinforce the need to adapt academic assessment strategies to mitigate the impact of AI use in written assignments, thus ensuring fairness in assessment processes.

## CONCLUSIONS

The use of Large Language Models (LLMs) in education poses unprecedented challenges for assessment and academic ethics (Yikang et al., 2023). This study has demonstrated the effectiveness of a multi-metric approach to detecting academic dishonesty, integrating textual similarity analysis techniques with specific metrics to identify the use of artificial intelligence in the production of student responses. The application of indicators such as perplexity, sentence-length variability, and lexical complexity has proven robust for distinguishing AI-generated responses from those written by humans.

The results reveal a transformation in how students approach the production of academic content in the age of artificial intelligence. While access to LLMs can offer opportunities for assisted learning, their unregulated use raises ethical concerns about the authenticity of responses and the integrity of the assessment process.

The high accuracy of the detection system developed provides teachers with more effective tools for verifying responses. However, the underlying challenge is how to educate students about the ethical use of AI without discouraging its potential as a pedagogical tool.

From an educational and ethical perspective, academic dishonesty not only compromises the validity of assessment processes but also undermines the development of critical competencies and autonomous reasoning skills. In this context, it is essential to rethink teaching and assessment strategies as the availability of generative AI grows.

Pedagogical review of assessment strategies: It is recommended to implement assessment methods that reduce the risk of AI misuse, such as oral tests, in-class written essays, and personal reflection exercises. These strategies can promote more authentic assessment focused on individual knowledge production.

*Emphasis on ethical training in AI use:*

It is imperative to integrate digital and ethical literacy into the curriculum to guide students in the responsible use of language models. It is necessary to differentiate between AI as a learning support tool and its misuse in assessment contexts.

*Continuous monitoring and adjustment of detection thresholds:*

The constant evolution of LLMs requires detection systems to be adaptable and updatable, minimizing the risk of false positives while maintaining high accuracy in identifying AI-generated responses.

In terms of future lines of research, it is necessary to continue exploring the evolution of AI models and their impact on higher education and academic training. In addition, optimizing detection algorithms and adapting assessment strategies to an environment in which artificial intelligence plays an increasingly central role in learning are key aspects of ensuring academic integrity without restricting technological innovation.

This study contributes to reflections on the ethical challenges that arise from the incorporation of AI in education and highlights the need to strike a balance between adopting new technologies and preserving the fundamental principles of autonomous and critical learning. The responsible integration of AI into education should prioritize the development of genuine skills in students, ensuring that technology serves as a facilitator of learning rather than a substitute for human analysis and reasoning.

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**AUTHOR CONTRIBUTION**

*Conceptualization:* Hector Cuesta-Arvizu, Enoc Gutiérrez Pallares.
*Writing – initial draft:* Hector Cuesta-Arvizu, Enoc Gutiérrez Pallares.
*Writing – review and editing:* Hector Cuesta-Arvizu, Enoc Gutiérrez Pallares.

# Chapter 10 / Capítulo 10

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# Process of integrating AI into research skills training in the Venezuelan university context

## Proceso de integración de la IA en la formación de competencias para la investigación en el contexto universitario venezolano

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### ABSTRACT

The research was conducted using a qualitative approach, with the purpose of understanding the stages of the AI integration process in research competency development within the Venezuelan university context. A hermeneutic phenomenological design was employed, allowing for the exploration of faculty perceptions regarding the challenges presented by AI. Eight (8) university faculty members from different areas of knowledge participated in the research. These faculty members had experience as teachers, tutors, and jury members, and held administrative positions in the university hierarchy (associate and full professor) at four Venezuelan universities: UPEL, UC, UNEFA, and UNELLEZ. Semi-structured interviews were used, which were processed until category saturation was reached, structured, and triangulated among key informants, authors, and researchers. The findings of this research reveal that the process of integrating AI into research skills development within the Venezuelan university context can be outlined in five stages experienced by the teacher: resistance to change, modification of limiting beliefs, teacher training in AI tools, transformation of classroom practice, and participation in the evaluation phase as a tutor and jury member. These stages correspond to a process that the teacher goes through, often without being aware of it.

**Keywords:** Research Skills; Artificial Intelligence; Training In Research Skills; Integration Process.

### RESUMEN

La investigación se llevó a cabo con un enfoque cualitativo, con el propósito de comprender Cuáles son las etapas del proceso de integración de la IA en la formación de competencias para la investigación en el contexto universitario venezolano. Se empleó un diseño fenomenológico hermenéutico, que permitió explorar las percepciones de los docentes ante los desafíos que presenta la IA. En la investigación participaron ocho (8) docentes universitarios de diferentes áreas del conocimiento, con experiencia como docente, tutor, jurado y con categorías administrativas en el escalafón universitario de asociado y titular de cuatro universidades de Venezuela UPEL, UC, UNEFA, UNELLEZ. Se empleó la entrevista semiestructurada, la cual fue procesada hasta saturar las categorías, estructurar, triangular entre los informantes claves, autores e investigadoras. Los hallazgos de esta investigación revelan que el proceso de integración de la IA en la formación de competencias para la investigación en el contexto universitario venezolano se puede esquematizar en cinco etapas vividas por el docente: la resistencia al cambio, modificación de las creencias limitantes, la formación docente en herramientas IA, la transformación de la práctica en el aula y la participación en la fase evaluativa como tutor y jurado. Estas etapas corresponden a un proceso que el docente va transitando sin que muchas veces sea consciente de ello.

**Palabras clave:** Competencias para la investigación; Inteligencia artificial; Formación en competencias investigativas; Proceso de integración.

## INTRODUCTION

With the arrival of artificial intelligence (AI) in university research processes, a transformation has occurred in the role of the university teacher, leading to significant changes in the skills of both teachers and students. This process not only involves considering technical or methodological aspects; rather, it is complex and involves an emotional, cognitive, and epistemological journey. In this regard, Cárdenas (2023) proposes clear criteria for validating the use of AI, including the explicit declaration of the use of generative tools, the reconstruction of the analytical process, and the delimitation of the scope of AI, differentiating between technical assistance and epistemological decisions.

This leads to a rethinking of the role of the researcher and intellectual production methods. From an ontological perspective, university teachers face the challenge of redefining their role as researchers. As Corona (2025) mentions, AI "does not displace the teacher, but rather reinscribes them as an active epistemic agent" (p.111). This transformation requires deep reflection on professional identity, the ethics of technology use, and responsibility in the training of new researchers.

In this sense, the epistemological dimension of integrating artificial intelligence (AI) into university research must be approached from a critical, situated, and dynamic perspective that recognizes the complexity and probabilistic nature of the knowledge generated by automated systems. As Román (2024) reveals, the field of AI epistemology is complex and multifaceted. Pérez (2024) points out that AI represents a confluence between classical epistemology and current technological challenges.

Given this scenario, university professors are allowed to access new techniques, broaden their research approaches, foster innovation in the design and development of scientific projects, and optimize their research skills, as proposed by Aguirre et al. (2024), research skills enhanced by artificial intelligence include the ability to automate data management and analysis, optimize resources to achieve more efficient results, and improve information gathering and evidence presentation processes. It is here that university teachers face the challenge of redefining their role, not only as transmitters of information but also as guides in the development of research skills. This transformation requires a comprehensive review of traditional teacher functions, particularly regarding research training (Marcelo, 2009).

Research training in contexts where AI enables teachers to adopt new critical, reflective, and strategic positions, as Van Manen (2003) points out, the pedagogical act must recover its experiential and ethical dimensions, particularly when technologies mediate the relationship between the individual and knowledge. In this sense, teachers must play an active role in creating hybrid environments that integrate face-to-face and virtual experiences, the human and the algorithmic, without losing sight of the ethical and formative dimensions of their work (Coll, 2004).

In contexts where AI is present, competencies must be expanded to include understanding algorithms, analyzing data biases, and using digital tools to explore, contrast, and visualize information. That is why it is essential to develop research skills, which involve not only mastering techniques but also formulating relevant questions, selecting reliable sources, and critically constructing knowledge (Zabalza, 2007). For their part, Arzuaga et al. (2023) assert that research skills must be developed in a cross-cutting manner, integrating autonomous thinking, theoretical foundations, and territorial sensitivity.

In this vein, Cárdenas (op. cit.) asks: How should academia adapt to the rise of generative AI? This opens the door to a profound reflection on the research skills that should be promoted in students and supported by teachers. From an experiential perspective, the process of adaptation of university teachers to the use of generative AI, specifically in terms of the development of research skills, whether transversally in the different subjects or curricular units of an academic degree program, or in a research methodology course.

This is where the use of artificial intelligence in education raises ethical and epistemological dilemmas that we cannot ignore, as Bunge (2009) reminds us that all scientific practice must be guided by ethical principles that ensure the social responsibility of knowledge. In short, developing research skills with AI is not just about learning to use tools, but about transforming the way we understand knowledge, the subject being researched, and the environment in which it is produced.

University teachers are called upon to lead this transformation from a critical, ethical, and situated position, capable of integrating technology without losing sight of the humanity of the research process. This vision aligns with the principles of critical pedagogy, which sees education as an act of liberation and transformative consciousness, where Freire (1997) argues that teachers must promote educational practices that stimulate reflection, dialogue, and critical action. In the current context, this idea takes on special relevance, as AI can be used both to empower and to control.

That is why teachers have a responsibility to train students to question the assumptions behind data, interpret algorithmic discourses, and construct contextualized knowledge. As Giroux (2001) points out, critical teachers not only transmit knowledge but also create the conditions for students to become active protagonists in their own education.

This allows us to propose, as a central axis, the understanding of how AI modifies the ways of thinking, validating, and producing knowledge in the university environment, requiring teachers to reconfigure their ontological (as subjects who investigate) and epistemological (as mediators of knowledge) positions. In this sense, it is necessary to listen to the voices of teachers undergoing this transformation through the critical, reflective, and situated experience of their research practices. These findings are drawn from experiences with AI, seeking to understand how teachers can take on an active, ethical, and relevant role in building research skills in the age of artificial intelligence.

## DEVELOPMENT

The research used a qualitative approach to examine the stages of integrating AI into the development of research skills in the Venezuelan university context. This approach helps us to capture the experiences, meanings, and challenges that arise in current educational practice.

The qualitative paradigm, according to Hernández et al. (2022), seeks to interpret complex phenomena from the perspective of social actors, which is relevant for understanding the process that teachers are undergoing in relation to AI. A phenomenological-hermeneutic design was selected to explore teachers' perceptions of the challenges posed by AI and to understand the deeper meaning of human experiences, especially in times of professional transformation, as proposed by Van Manen (Op. cit.). Eight (8) university teachers from different areas of knowledge participated in the research, with experience as teachers, tutors, examiners, and in administrative positions in the university hierarchy as associates and tenured professors at four universities in Venezuela: Universidad Pedagógica Experimental Libertador (UPEL), Universidad de Carabobo (UC), National Experimental Polytechnic University of the National Armed Forces (UNEFA), and National Experimental University of the Western Plains "Ezequiel Zamora" (UNELLEZ).

For collecting information, the primary technique used was the semi-structured interview. Kvale and Brinkmann (2015) highlight that this type of interview provides access to participants' contextualized knowledge, especially in educational research. The interview script, as an instrument, was developed based on theoretical categories and preliminary findings to capture in-depth narratives.

The criterion of theoretical saturation, as suggested by Strauss and Corbin (2002), was applied to ensure that the emerging categories reflected the diversity of perspectives on the process by which teachers incorporate AI into their research practice. This allowed us to identify patterns in the discourse and contrast the experiences of teachers in different disciplinary areas, professional backgrounds, and levels of familiarity with AI tools.

Based on the teachers' interviews, the following categories emerged.

**Change from a traditional role to an emerging role**

According to key informants, it is necessary to redefine the traditional role of the teacher as a simple transmitter of information, limited to administering the contents of an academic program, redirecting it in the following dimensions:

*Curator of knowledge*

A professional who actively searches different sources of knowledge, filters, selects, and organizes information, giving meaning to the vast amount of information available through critical analysis. At the same time, they must become defenders of cognitive sovereignty, understood as the ability of a person, community, or nation to control and manage their own knowledge, thinking, and decisions (Ruocco, 2025), which, when developed, allows each person to develop their own information filtering systems and choose when to submit to that flow of information, being able to use the benefits of the current era to their advantage. Contributions such as that of Acevedo et al. (2025) reinforce the idea that teachers, by playing an active role in digital knowledge management, are guiding critical thinking in the face of artificial intelligence, as they must not fall into blind dependence on its results.

*Strategic*

They must be able to guide complex thought processes, model research practices that adapt to the context, and foster communities of practice that cross disciplines. In this sense, teachers become managers of educational processes that combine technology, ethics, and critical thinking, a vision shared by Román et al. (2024), who argue that an epistemological reconfiguration is needed, with artificial intelligence asking us to rethink how we think as educators because it is changing the way we teach.

*Human*

As mediators in the management of these technologies and preservers of the knowledge that makes us human and constantly evolving beings, teachers are willing to create research experiences that make the most of AI's potential, without losing sight of the researcher as the center of the process. From a humanistic perspective, Santos (2001) describes the teacher as a builder of meaning and a craftsman of the soul, capable of connecting culture with life, preserving the knowledge that forms human identity. Likewise, Meirieu (2007) states that teachers must act as ethical bridges between knowledge and students, committing themselves and ensuring that technology does not replace the pedagogical relationship.

*Ethical*

Teachers become ethical and critical mediators between students and emerging technologies, enabling them to take a position on a situation and argue their case. Their guidance directs the use of AI in the creation of knowledge, thus avoiding the reproduction of inequalities or the manipulation of results. Without ethical guidance, artificial intelligence can perpetuate biases and errors (Camacho et al., 2025). Therefore, teachers must adopt a reflective, formative stance to ensure the responsible use of these technologies.

The contributions of key informants allow us to link this category to the first two stages of the AI integration process for teachers: resistance to change and modification of limiting beliefs. In the case of the former, it may arise when faced with the possibility of taking on the emerging role, when teachers do not want to leave their comfort zone, or in other cases, when they have difficulty accessing technological resources, including up-to-date hardware and a stable and fast internet connection, which is particularly prevalent in countries or regions with more vulnerable socioeconomic and technological situations, widening the gap between regions in terms of knowledge generation.

According to the informants, teachers need to recognize limiting beliefs, such as: AI encourages laziness, AI will replace teachers, or books are no longer necessary. Another dilemma that teachers may experience at this stage is: Who am I evaluating? This question will become clearer once teachers begin training in the educational use of AI. Once these beliefs are recognized, acknowledge that they are not helpful if you want to move forward with this historic challenge in education, and through neuroplasticity, change them. In agreement with Doidge (2007), he argues that the human brain has an incredible ability to change and adapt, a phenomenon known as neuroplasticity. This ability allows us to modify our patterns of thought and behavior through new learning experiences. This ability is essential for teacher to redefine their role, reevaluate their beliefs, and train themselves in the didactic use of AI from an ethical, reflective, and contextualized perspective.

**Implications of the emerging role that teachers must fulfill in an AI-mediated context**

Key informants agree that one of the most significant challenges is the need for continuous updating in different areas, on the one hand, for the management of technical tools, as it is undeniable that advanced digital literacy is crucial, not only for managing tools, but also for understanding algorithms, their limitations, biases, and structures. Teachers can appropriate these tools by being active researchers who practice AI for knowledge generation and participate in research groups. In this way, they can develop the ability to build collaborative networks, both inside and outside the university, that allow for the sharing of best practices, joint reflection, and the consolidation of an inclusive and relevant research culture. This would constitute the third stage of the integration process, in which teachers have already overcome their resistance to change and transformed their limiting beliefs, have trained themselves at the epistemological and methodological levels, and are beginning to apply AI in their own research.

In this context, González et al. (2022) emphasize that the research culture of teachers in Latin America is strengthened when participation in digital academic communities is encouraged, emerging technologies are used in a contextualized manner, and a connection is established between local and global knowledge. In this way, teachers not only receive training in the technical use of AI but also incorporate it as a tool to enrich their educational, critical, and transformative roles. However, the informants also highlight the need for training in philosophical and pedagogical frameworks that enable them to redefine their roles within a hybrid knowledge ecosystem that combines face-to-face and virtual activities, unified in the pursuit of knowledge construction. This requires a change in the roles of teachers and students, establishing guidelines for mediation through technology and emphasizing the development of critical thinking (Díaz & Benitez, 2025). In this sense, epistemological thinking becomes fundamental: researchers need to question the assumptions behind the data generated by AI.

**Transformation of classroom practice**

The findings show that once teachers have overcome their resistance to change and modified their limiting beliefs, they begin to actively shape and practice research in partnership with AI so that, with their knowledge and experience, they can accompany students in the optimal learning of AI for research, which will occur in stage four of the integration process. Especially in hybrid ecosystems, where face-to-face and virtual activities are combined, one question teachers may ask themselves is: What types of activities can be used to promote the appropriate use of AI in university education? For students to appropriately use tools to integrate AI, the teacher who accompanies them must have done so beforehand, enabling them to design activities that develop the skills students require.

In line with the above, key informants believe that teaching practices need to be reformed from planning to the development of knowledge management strategies, with support from an AI application that can manage content, videos, images, and other actions, serving as a starting point for generating critical thinking. This finding coincides with Molina et al. (2025), who argue that teaching practices need to be rethought, from planning to knowledge management, incorporating AI applications that act as a starting point for fostering critical thinking. Making students reflect that if they only think about requesting information from AI and cutting and pasting it, its application makes no sense. However, it is valued as a generator of new ideas, a corrective assistant, and support for textual production through face-to-face human review. In that case, the dimension shifts from searching for information to evaluating content and selecting it based on its relevance by a human.

Teaching practices focused on a logic of co-construction of knowledge require teachers to act as facilitators of environments for exploration and analysis, rather than simply giving direct instructions. This involves redesigning learning environments so that students can develop research skills to interpret, contrast, and reconfigure knowledge based on the information these tools generate, promote metacognition, integrate active methodologies such as project-based learning, and foster an ethic that enables them to discern the responsible use of AI.

This new paradigm involves flexible, adaptive educational practices focused on developing skills to formulate relevant questions, choose reliable sources, and construct solid arguments, connecting theory and practice, thus transforming the classroom into a laboratory of thought, where AI enhances, but does not replace, the human capacity for purposeful inquiry. Santana (2025) argues that it is fundamental to train teachers oriented towards artificial intelligence with a critical and reflective attitude, so that they can integrate these technologies without losing sight of the ethical, pedagogical, and humanistic principles that underpin educational practice. Another fundamental aspect is to emphasize the formulation of relevant, contextualized, and ethically sound research problems, while relying on AI to explore trends, generate hypotheses, or visualize data, yet remaining aware that the criteria for constructing research remain human.

**The evaluation phase in AI: participation as a tutor and evaluation panel**

Ideally, reaching this stage requires having completed the previous ones, although it is known that some teachers evaluate without having taught research or without being active researchers. In everyday practice, a teacher who knows their students can recognize how they express themselves, both in colloquial and technical language, and therefore will easily be able to differentiate a text produced by a simple AI search.

Traditionally, one of the main difficulties' students faced in conducting their research was writing their ideas coherently. Language is considered the instrument through which researchers express knowledge as they have apprehended it through their life experiences: knowledge, experiences, perceptions, and other subjective elements that leave the researcher's personal mark on the product they deliver (Marín, 2019). When AI is used, a text may contain unfamiliar terms to the researcher. This is where they must delve deeper, conducting new searches to clarify these concepts and make the writing more understandable for all readers to whom the research may be addressed, whether from a technical point of view or at an academic level. This educational approach strengthens research autonomy and ethical discernment in the use of emerging technologies (Camacho et al., Op. cit.).

This is where the challenge lies in teaching them to broaden the research process by reading the direct sources (books, scientific articles, blogs, among others) that appear in the AI search, rather than directly penalizing them with a grade. At first, the evaluating teacher must encourage the continuity of the process, inviting the student to complement their product with critical analysis that allows them to reconstruct the text and, above all, to demonstrate a deep understanding of the text they are presenting as their own work.

## CONCLUSIONS

The findings of this research reveal that the process of integrating AI into the development of research skills in the Venezuelan university context can be outlined in five stages experienced by the teacher, which are often passed through without the teacher being aware of it, some more easily and quickly than others.

The first stage is resistance to change, a defensive reaction to the unknown. Many teachers feel anxiety, mistrust, and a loss of control over teaching processes when faced with technologies that transform their traditional practices. This resistance should not be seen as denial, but rather as an adaptive response to the dissonance between their previous pedagogical frameworks and new ways of generating knowledge, as well as a lack of training in AI and institutional policies (López et al., 2025).

For Sánchez et al. (2025), resistance to change often stems from limiting beliefs about the supposed dehumanization of knowledge or from fear of losing control over academic processes. In this sense, the second stage involves addressing limiting beliefs; once the initial resistance is overcome, teachers begin to question their beliefs about research and technology. According to Torres and Arroyo (2025), this involves recognizing the educational potential of AI, opening up to new forms of tutoring and assessment, and redefining the role of teachers as critical mediators. It is essential to address these beliefs from a formative perspective, recognizing artificial intelligence (AI) as a support tool rather than a replacement for critical thinking or ethical judgment. Changing these limiting beliefs requires creating spaces for teacher reflection in which the role of AI in knowledge production is discussed, its biases examined, and an attitude of informed openness fostered.

The third stage is teacher training in AI tools. Cárdenas (op. cit.) states that to get the most out of AI in university research, it is essential to train teachers to use tools that facilitate the research process, such as writing assistants, source verifiers, and simulators. This phase focuses on acquiring both technical and methodological skills, always within an ethical and contextualized framework. In addition, this phase requires teachers to stay up to date with technological advances, develop advanced digital literacy, manage collaborative environments, and critically evaluate the results produced by AI, all of which are key to ensuring academic quality. Training programs for teachers have been launched that include simulators, writing assistants, source verifiers, and collaborative environments (Oseda et al., 2025).

The fourth stage, the transformation of the classroom process, whether face-to-face or virtual, is in full swing and goes beyond the technical because it is deeply pedagogical. It involves a new way of understanding teaching as a dialogical, ethical, and contextual process. Loayza (2023) points out that to achieve this transformation, it is essential to break down the technological, organizational, and attitudinal barriers that hinder the effective integration of AI in the classroom. Teachers are reinventing their teaching strategies by incorporating tools such as AI-generated mind maps, automated rubrics, interview simulations, and case studies. Pedagogical innovation projects have been launched that use AI to personalize learning and encourage student self-regulation (Kroff & Ferrada, 2024).

In addition, AI facilitates adapting content to different learning styles, generates personalized feedback, and stimulates active student participation. In this new stage, teachers are consolidating their role as designers of educational experiences that integrate technology, ethics, and context.

Finally, the fifth stage focuses on the teacher's role as a tutor and evaluator of AI-based research projects. At this point, teachers must ensure the traceability of the research process, the originality of the products, and the theoretical basis behind each methodological decision. Cárdenas (Op. cit..) suggests clear criteria for validating the use of AI in theses, including an explicit declaration of the use of generative tools, the reconstruction of the analytical process, and the integration of authentic scientific literature. From an ethical perspective, this stage requires skills such as mediation, active listening, and critical and ethical evaluation, recognizing the student as an epistemic subject in dialogue with technology. In the era of generative AI, university teachers not only teach but also accompany, transform, and ensure the ethics of knowledge. It is essential to prepare teachers to integrate philosophical and pedagogical frameworks that transform their roles in hybrid learning environments, where artificial intelligence and face-to-face teaching combine to enrich the educational process. (UNAH, 2025)

Inga and Castro (2024) suggest that support should focus on fostering research autonomy, ensuring methodological transparency, and integrating authentic scientific literature. In this context, teachers become guarantors of academic quality in environments where AI plays an important role. Ultimately, this stage reinforces the transformation of the teacher›s role as an epistemic agent, where ethical support not only endorses the use of AI but also promotes a research culture grounded in responsibility, creativity, and a commitment to knowledge. Atencio (2023) points out that the use of AI in educational research must be guided by ethical principles that safeguard academic integrity and encourage critical thinking in students.

Although this process presents challenges, it also opens doors to new opportunities for pedagogical innovation, technological equity, and academic sustainability, considering the voices of the teachers who report on the following challenges brought about by the integration of AI in the training of researchers:

1. Addressing uncritical dependence, where students unquestioningly trust what AI produces without verifying sources or processes, through a transformation that is not only methodological but also ontological: teachers must create spaces for complex thinking where AI acts as an ally, not a substitute.
2. Teacher training and gaps in access and training, especially in Latin American contexts, where not all teachers are equipped to integrate these technologies critically. The challenge of constant information, constant updating, and the struggle against time and obsolescence, because every day new contributions, updates, and emerging, innovative tools are promoted that leave behind what is learned and require the development of new, dynamic, changing skills at an impressive pace. The challenge is to keep up to date.
3. We must also consider the ethical challenges that arise: from data manipulation to the perpetuation of biases, AI can intensify inequalities if its use is not regulated. The issue of authorship is also relevant, as artificial intelligence can blur the researcher's identity if clear criteria for its co-creation are not established.
4. Tension between the speed offered by AI and the depth required by rigorous research. Training researchers in this environment requires a pedagogy that values pause, discernment, and applied ethics.
5. Cultivating a broader scientific narrative, capable of communicating findings in multimodal formats that connect with current generations characterized by digital culture.

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# Chapter 11 / Capítulo 11

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# AI Literacy for Research: Study of Primary School Teachers in Greater Caracas

# Alfabetización en IA para la Investigación: Estudio en Maestros de Educación Primaria de la Gran Caracas

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## ABSTRACT

This paper analyzes the integration of Artificial Intelligence (AI) as a support tool in pedagogical research practices by primary school teachers in Greater Caracas, based on workshops developed in both public and private educational institutions. To this end, it adopted a mixed approach, with a predominance of the qualitative component (systematization of experiences) for understanding the exchange with teachers (Mera, 2019), and a quantitative component (descriptive study) for recording and analyzing the use of Generative AI tools. The main conclusions include: a) research by primary school teachers is practically non-existent prior to direct training intervention, b) the initial diagnosis, convergent in both private and public institutions, revealed an incipient approach and a general lack of knowledge about the effective integration of these technologies, and c) the study corroborates that the research carried out by primary school teachers is not theoretical or basic in nature, but deeply pragmatic and oriented towards immediate pedagogical action.

**Keywords:** Literacy; Artificial Intelligence; Primary Education; Research; Teachers; Greater Caracas.

## RESUMEN

El presente trabajo analiza la integración de la Inteligencia Artificial (IA) como una herramienta de apoyo en las prácticas de investigación pedagógica por los maestros de primaria en la Gran Caracas a partir de talleres desarrollados en instituciones educativas tanto públicas como privadas. Para ello adoptó un enfoque mixto, con predominio del componente cualitativo (sistematización de experiencias) para la comprensión del intercambio con los maestros (Mera, 2019), y un componente cuantitativo (estudio descriptivo) para el registro y análisis de la utilización de herramientas de IA Generativa. Entre las principales conclusiones se señalan: a) la investigación por parte de los docentes de primaria es prácticamente inexistente antes de una intervención formativa directa, b) el diagnóstico inicial, convergente tanto en instituciones privadas como públicas, reveló un acercamiento incipiente y un desconocimiento general sobre la integración efectiva de estas tecnologías y c) el estudio corrobora que la investigación practicada por los maestros de primaria no es de naturaleza teórica o básica, sino profundamente pragmática y orientada a la acción pedagógica inmediata.

**Palabras clave:** Alfabetización; Inteligencia Artificial; Educación Primaria; Investigación;

Maestros; Gran Caracas.

## INTRODUCTION

The presence of AI in education has skyrocketed in recent years. Evidence of this can be found in the specialized literature, which has been on the rise, focusing not so much on challenges and tensions but rather on developing proposals for training, literacy, and ethical and responsible use. It is important to note that literacy implies knowledge, while application corresponds to skills (Chiu, Ahmad, Ismailov, & Temitayo, 2024). In addition to these points, there has been interest in some reflections on levels of training, where one path indicates the recognition of AI in the field of education, and, after this step, where resistance is addressed, it is possible to achieve literacy (Peña, 2023).

However, within the narratives of international organizations, UNESCO (2023, 2025) insists on bringing this emerging technology to everyone, provided that it is linked to ethics, while Gómez, Del Pozo, Martínez, and Martín del Campo (2020) call for the common good in the regions. Both coexist coherently with the proposals. However, how has research been presented in teaching? This is a broad question with many answers. For example, the role of teachers has undergone significant changes in recent decades. Especially in Latin America, qualification and recognition have been promoted through research and innovation in educational practices (Aguilar & Cifuentes, 2021/ Barragán, Castilla, Martínez, Ruiz, Franco, & Montoya, 2009). In line with this, national objectives have been identified, such as the 2016–2020 Sectoral Education Plan in Bogotá, Colombia, which seeks to build an educated city. Similarly, the National Fund for the Development of Peruvian Education (FONDEP) seeks to implement Participatory Action Research in Education (IAPE) in public schools (Aguilar & Cifuentes, 2021/ Santandreu, 2019).

Including research in a state's proposals implies valuing education and seeking necessary approaches to coexisting problems. While this implies considering the level of teacher preparation, it is also necessary to associate them as professionals in constant training. Only then can one consider, for example, one criterion for affordable education (teacher training). Based on this consideration, it is possible to find some data in South America. It is worth noting that in Colombia, it is estimated that around 30 % of teachers have a postgraduate degree (Universidad Autónoma de Bucaramanga - UNAB, n.d.), in Bogotá, more than 60 % of teachers have a master's degree, and more than 120 have doctoral training (Aguilar & Cifuentes, 2021); while in Venezuela, according to Fundaredes (2024), 41 % of teachers have a specialization.

Although the figures above reflect some realities, the status of teachers as researchers must be defended within educational institutions. This observation is based on the premise that research conducted by school teachers is often "dragged along and co-opted by higher education institutions" (Aguilar & Cifuentes, 2021, p. 135), thereby rendering invisible the knowledge produced in school contexts.

## DEVELOPMENT

In the context of Artificial Intelligence (AI), some ideas associated with direct pedagogical practice and professional research and development practices have been identified. These are two distinct and complementary dimensions. However, how has each been viewed? Camones, Bardalez, Pérez, and Padilla (2023) indicate that classroom educational practices primarily serve as an assistant or collaborator to the teacher, transforming the dynamics of teaching and learning. Here, we are already looking at the appropriation of AI tools within the processes.

In UNESCO's narrative (2025), it is also common to identify some challenges associated with learning in the age of AI, one of which is the personalization of learning. In recent years, there has been an emphasis on using educational agents for subjects, thus going beyond simply consulting chatbots for planning student-oriented activities. With this new level, not only are content and activities adapted to students' individual needs (Montes, n.d.), but assistance can also be provided when needed.

While teachers' experiences in creating personalized activities for students have been identified, neurodivergent students have also been taken into account. Consequently, thanks to AI, there has also been a commitment to understanding and inclusion in the classroom. In this regard, it is worth noting that: "60 % of primary and secondary school teachers admit to now using AI to plan lessons, communicate with parents, and assist with grading" (Kozak, 2025, para. 7).

AI in education has come to be understood in terms of its possibilities for reflective actions. This arc involves understanding this technology from the perspectives of teaching, learning, and assessment processes. Interest in studying each process continues. From interpretive horizons, it is possible to review proposals and searches.

Therefore, it is not just a matter of whether to use a tool and of being clear that offerings are constantly updated at the mercy of changing consumer tastes, but rather that communication and technological skills need to be developed to respond to current dynamics. In this regard, concerns about automating teachers' administrative tasks have likely been gradually overcome in light of new issues.

The use of generative tools, such as ChatGPT, Gemini, or Copilot Chat, has already become a trend. Indeed, statistics from AIPRM (n.d.) indicate that the most common AI tools used in education by teachers are AI-powered educational games, which are employed by more than half (51 %) of teachers. As a result, interest is shifting to new areas, such as AI gamification. Teachers must therefore adopt a proactive stance that adapts the pedagogical approach to this new reality (Bustamante & Camacho Bonilla, 2024). At the same time, reflecting on the possible consequences of working with AI will likely ensure its responsible use in fields of action.

Beyond the challenges of creating effective, clear, and specific *prompts* (Montes, n.d.), it is necessary to specify how it is being used in the field of research. Is it only for searching or for data analysis? It is worth pausing to consider this particular issue. On the one hand, it is well known that AI is being incorporated into the research practices of teachers and university researchers studying teaching (Camones, Bardalez, Pérez, & Padilla, 2023). It is worth noting that AI is also a recurring theme in teachers' research. In Bogotá, for example, it is mentioned in 47.2 % of the cases analyzed (Aguilar-Forero & Cifuentes, 2021). Award-winning research has even been identified, such as the case of the AI-based tool for assessing learning in constructionist environments (Aguilar-Calderón, 2023).

Regarding AI research in education, adoption is still in its infancy, marked by significant structural challenges and knowledge gaps (Reza & Guemez, 2024).

More specifically, the incorporation of AI into education poses significant challenges that slow its full integration into classrooms (Bustamante & Camacho, 2024; Solano, 2025). More specifically, in Venezuela, the situation of AI in the basic education system shows a limited presence, although it is observed that teachers are exploring the technology. According to

Duque-Rodríguez, Piña-Ferrer, and Isea-Argüelles (2025), it is rated as having little presence in the teaching processes of the Basic Education Subsystem (which includes Early Childhood, Primary, and Secondary Education), with an average of 2.54. This contrasts with the study by Fundación Telefónica (2025), which revealed that “4 out of 10 teachers already use AI tools in their teaching practices” (paragraph 1).

In light of these findings, it is worth paying attention to the statistics and assessing digital literacy, as recommended by UNESCO (2025), in addition to “managing, understanding, integrating, communicating, evaluating, and creating information through the safe and relevant use of digital technologies” (paragraph 5). However, do primary school teachers in Caracas conduct research using AI?

Research by primary school teachers in Latin America has traditionally focused on action research (AR), the systematization of experiences to transform their own teaching practice, as evidenced in publications on educational websites and in magazines. However, is AI being incorporated into this process as methodological support for research?

This study sought to analyze how primary school teachers in Greater Caracas are integrating (or not) Artificial Intelligence (AI) as a support tool in their pedagogical research practices. To this end, the following specific objectives were set: 1. To determine which specific AI tools (if any) are being used and for which phases of the research process, 2. To identify the main challenges faced by primary school teachers, and 3. To design proposals or recommendations to promote the practical and ethical integration of AI in research.

## METHOD

The study adopted a mixed-methods approach, with a predominance of the qualitative component (systematization of experiences) to understand the exchange with teachers (Mera, 2019), and a quantitative component (descriptive study) to record and analyze the use of Generative AI tools.

In the first qualitative approach, emphasis was placed on the systematization of experiences as a research method for producing knowledge through meetings with primary school teachers in Greater Caracas. In this sense, the aim is to: a) Reconstruct and narrate the facilitator’s journey and the exchange with teachers from primary schools in Greater Caracas, b) Critically interpret the experiences, identifying the successes, challenges, learnings, and knowledge generated in the interaction, and c) Produce knowledge based on the educational practice experienced.

The scope of the systematization of experiences as a method is presented in the following terms: it is a matter of understanding them within the framework of a complex historical process involving different actors, taking place in a specific economic and social context, and at an institutional moment of which human beings are a part. Systematizing experiences, therefore, means understanding why this process is developing in this way, understanding and interpreting what is happening, based on an ordering and reconstruction of what has happened in this process (Mera, 2019, p. 103).

Based on this scenario, the facilitator’s field diary/logbook was used as a technique, which constitutes the primary source for reconstructing the journey, recording observations, reflections, informal dialogues, and decisions made in each school, which were then transcribed and categorized in order to identify emerging themes, patterns in the experiences, and the main lessons learned or difficulties encountered. However, we did not neglect the recommendations of Castañeda (2014), who points out that systematization requires a documentary review based on the experience itself, which can provide various forms of support for the work carried out and its analysis process, including photographs, educational materials, and records of group work. Furthermore, as Jara (2018) states, it is necessary to “develop the capacity for observation and perception, and educate our sensitivity to the many details that permeate what happens to us in everyday practice and speak to us from there” (p. 107).

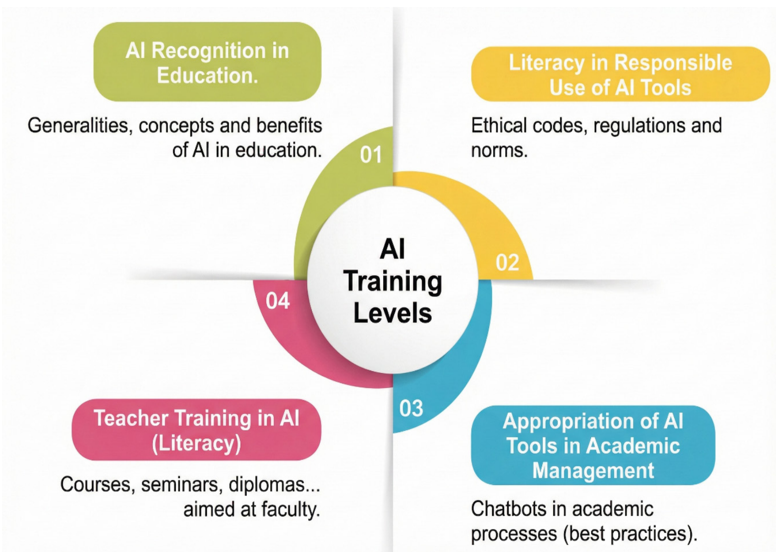
On the other hand, the second approach uses the set of interactions, exchanges, and reflections developed by the facilitator with primary school teachers in Greater Caracas as its unit of analysis. It also includes the educators who participated in the exchange and whose practices were influenced by or reflected the application of the tools.

In this case, a structured instrument was used as an information-gathering technique and applied to teachers in order to report how regularly they use the specific tools shared by the facilitator and in what contexts. In this sense, the data will be presented using frequency distribution tables and graphs (bar charts, pie charts) to describe the intensity and scope of the use of the tools.

Finally, to ensure credibility, sources were triangulated (facilitator, teachers, documents). Transferability is also ensured by providing a detailed description of the context of Greater Caracas and the facilitator’s journey, allowing other researchers to evaluate the applicability of the results.

## ANALYSIS AND RESULTS

In accordance with Peña’s (2023) proposal on levels of training in Artificial Intelligence (figure 11.1) and in line with outreach activities, assistance to schools focused on teacher training. Specifically, the fourth level of this proposal concerns teacher training in AI. However, the actions carried out did not necessarily cover the third level of the proposal, which corresponds to the use of chatbots in academic processes.




**Note:** Taken from Peña (2023).

**Figure 11.1.** Levels of training in Artificial Intelligence

Initially, the approach was to target private institutions in vulnerable areas; subsequently, with the collaboration of other UCAB units, public school teachers were invited to two events. The first was part of Book Week 2025 (organized by the Abediciones team), and the second was a series of free workshops held during the Educational Innovation Congress (organized by the School of Education).

*UEP Colegio Agustiniano la Divina Pastora*

The school was registered with the Ministry of Education in 1936. In 1945, it abandoned the name “asilo” (asylum) and became known as UEP Colegio Agustiniano la Divina Pastora, the name it has since borne. It caters exclusively to girls from early childhood education through high school. The facilitator traveled to the school to teach two workshops. The first, on active methodologies, took place on November 5, 2024. The second workshop, focused on the use of Artificial Intelligence (AI) in document review processes, was scheduled for November 19, 2024.

Twenty-two teachers, accompanied by two academic coordinators, the head of Academic Control, the head of Guidance, and the principal, attended the school’s newly inaugurated laboratory. During the first phase (diagnosis), the participants indicated that they had a limited understanding of AI, limited to a single ethics talk. However, they pointed out a general lack of knowledge about the effective integration of Artificial Intelligence into teaching, learning, and assessment processes.

In the second phase (demonstration with chatbots), it was possible to: a) define a prompt based on the RITA model, b) develop a prompt for requesting a teaching strategy framed within active methodology for their course, based on working with a *prompt* guide, and c) review sources using AI tools for research (Elicit). Applications of AI tools in research were identified, as shown in the table 11.1.

**Table 11.1.** Application of AI-based tools in research

| Use of tools for research | Applications associated with research | Specifications |
|---|---|---|
| Elicit | Review of progress on topics for classroom projects. | “Having documents from specialized journals allows me to justify the projects” (informant 2)<br>“I would teach sixth-grade girls to play at being detectives, fishing for reliable sources” (informant 6) |
| | Preparation for interviews with parents | “I can stay up to date and suggest work plans to parents” (informant 10) |
| Chatbots | Use of the prompt guide | “After reviewing the guide, I now have a clearer understanding of the structure for requesting adjustments to the title of a research project” (informant 5) |
| Other tools (Slidesgo) | Preparing presentations for classroom projects | “The content is easy to find as long as you know what to look for” (informant 12) |

Given that only eighteen computers were available for the workshop and some teachers expressed difficulties with digital skills, it was decided to work in pairs (figure 11.2). This strategy was implemented specifically to encourage integration and mutual support among participants, as shown below.

Two materials were provided to the workshop participants. A link was sent to them via email, and the *Prompts Guide: Your Key to Exploration and Discovery* was shared as a writing reference. In addition, a Google Sites space for consultations called IAG for Educators was shared, where articles, presentations, and publications related to the workshops, authored by the authors, can be found.

**Note:** the photos were shared publicly on a social network (Instagram)
**Figure 11.2.** Teachers attending the workshop

Furthermore, work on classroom project topics was collected via email, and a sample was shared on Google Sites.

In terms of research, the classroom work indicated by the teachers followed three possible routes:

1. Review of literature to support classroom projects in line with current trends. In particular, primary school teachers considered that this added value to the work the girls carried out. For example, the SDGs are addressed at least once a year. In this regard, it is appropriate for teachers to be sufficiently prepared to address their students' concerns based on current information.
2. Preparation of materials to facilitate understanding (study guides, for example). From their searches in Elicit, they identified academic literature, and in Perplexity, they obtained guidance on adapting digital guides or workbooks for their work. Therefore, it is not enough to know what to look for; it is also necessary to know which suggestions are relevant as teaching and learning strategies.
3. Teaching proposals (derived from the literature review). Based on their interpretation of the documents, the teachers thought of games with digital tools for the girls and possible role-playing games.

*Public schools in Greater Caracas*

As part of Book Week 2025, the Abediciones team invited teachers from schools in Antímano, Carapita, El Paraíso, and San Juan to a workshop on AI. The data for this call was collected through a Google Forms questionnaire. Unlike the previous experience, two education students specializing in pedagogical sciences, who were taking the courses Research Methods II and Comparative Pedagogy, joined the team of facilitators to integrate them into work with schools in Greater Caracas.

83,3 % of the participants were women and 16,7 % were men (figure 11.3), reflecting the feminization of primary education in the country. Educational institutions such as Tito Salas, Simón Bolívar, UEN Andrés Bello, and Unidad Educativa Colegio Divino Maestro were present.

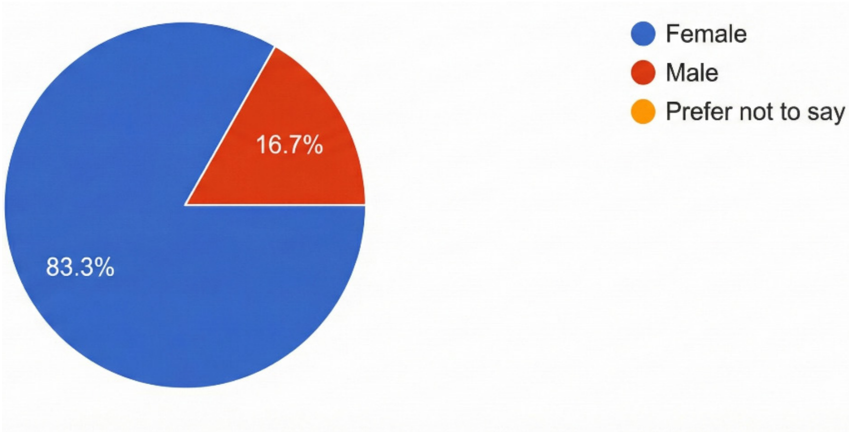



**Figure 11.3.** Percentage distribution by gender

This group of teachers was mainly represented by adults between 40 and 50 years of age, followed by those between 20 and 30 years of age (figure 11.4).

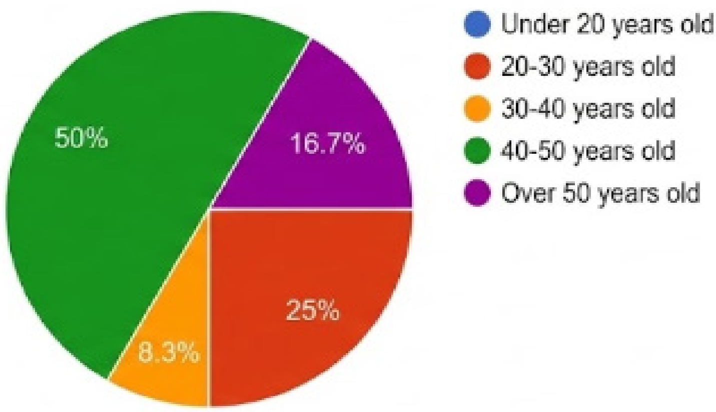



**Figure 11.4.** Ages of workshop participants

The workshop was conducted in two phases. The first phase involved an initial assessment using the Padlet digital tool, which yielded interesting responses. In addition to identifying the lack of initial AI training among teachers, it was found that they had not used any tools, even though they had the Perplexity app on their cell phones.

The introduction to AI began with the use of the RITA Model to construct prompts and was followed by a demonstration using Gemini, Copilot, and DeepSeek, with the participation of Professor Claritza and student Silvia Castro. Next, Sabrina León, a student in Research Methods II, explained to those present the research tools she had already used and adapted to possible applications in primary education.

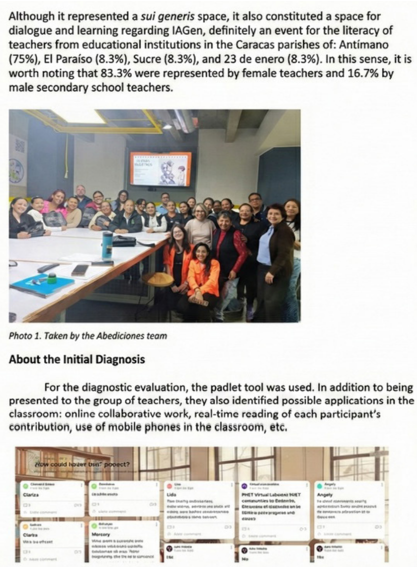
During the exchange, the teachers indicated at least three options, as shown in the following table 11.2.

**Table 11.2.** Applicability of research tools

| Tool | Indication | Challenge | Specifications |
|---|---|---|---|
| Elicit | Preparation of classes based on consultation of academic sources. | Translation of academic language into less technical language for the creation of teaching materials. | "I found it useful. I wish I had known about this tool when I submitted my specialization project" (informant 1). "I found what I was looking for for my science project very quickly and it was up to date" (informant 5). |
| Chatbot (Perplexity) | Teacher's assistant when you want to consult about a work plan. | Create the appropriate prompt to achieve the best results. | "Depending on the prompt, you can get a good planner for a project. I requested it and it worked well for me" (informant 4). "This tool is not only easy to use but also versatile" (informant 2) |
| Consensus | Consult sources in other languages to strengthen the work you want to develop. | Translation and interpretation. Relationship with the subject studied. | "As an English teacher, I have no problems, but what about a teacher who doesn't speak English?" (informant 3) "I think it's appropriate; it shows us the work sheets" (informant 5) |

Some difficulties associated with the use of specialized research tools were identified. For example, it was not easy to relate the topic to English searches, a limitation compounded by the teachers' reported lack of command of a second language. In view of these considerations, the DeepL.com translation tool should be used.

Figure 11.5 shows the group of workshop participants. It is important to note that this image was not only shared on the Mexican portal Tecnopia, but the university's red X network also actively promoted this exchange. It is presented below.



Although it represented a *sui generis* space, it also constituted a space for dialogue and learning regarding IAGen, definitely an event for the literacy of teachers from educational institutions in the Caracas parishes of: Antímano (75%), El Paraíso (8.3%), Sucre (8.3%), and 23 de enero (8.3%). In this sense, it is worth noting that 83.3% were represented by female teachers and 16.7% by male secondary school teachers.

*Photo 1. Taken by the Abediciones team*

**About the Initial Diagnosis**

For the diagnostic evaluation, the padlet tool was used. In addition to being presented to the group of teachers, they also identified possible applications in the classroom: online collaborative work, real-time reading of each participant's contribution, use of mobile phones in the classroom, etc.

**Note:** Photograph taken by the Abediciones team (left image) and excerpt from the review on Tecnopia (right image).

**Figure 11.5.** Teachers, students, and the Abediciones team attending the workshop

*Summary of categories*

After gathering the teachers' opinions in each workshop, the emerging categories were identified, as shown in figure 11.6.


*Note*: Image generated with Copilot

**Figure 11.6.** Emerging categories

First, AI literacy and digital competence among teachers (diagnosis) in both experiences (private and public schools) are convergent: teachers express an incipient approach, general ignorance about effective integration, and a lack of initial training in AI. Specifically, at Colegio Agustiniano, difficulties in digital skills were reported, and in public schools, teachers had not used any tools even though they were available.

This diagnosis coincides directly with the international literature. UNESCO (2023), in its preliminary guide on generative AI in education, emphasizes the urgency of developing AI skills for teachers, noting that most, like the participants in its study, are at an initial literacy stage. Similarly, Pérez Pérez and González de Pirela (2024) identify the urgent need to implement AI training programs, highlighting that "digital literacy" is the fundamental pillar for any successful pedagogical integration. Their findings therefore confirm that the skills gap is the critical starting point for teacher training.

Second, AI, as a teaching planning and preparation assistant, enabled teachers to identify AI applications to optimize their preparation processes quickly. For example, the use of Elicit for "reviewing progress on topics" and "preparing for parent interviews," and Perplexity as a "teacher's assistant when consulting on a work plan." The use of the RITA model and the "Prompt Guide" also points to the structuring of the planning process. These uses align with García-Peñalvo's (2023) description of the role of generative AI in improving administrative efficiency and as a support tool for subject preparation and lesson planning. The teachers in his study are using AI not only to create content, but also for their own continuing professional development.

Third, implementation challenges and adaptation strategies focus on: a) the skills gap, which was addressed with the peer work strategy, and b) the cognitive challenge of translating academic language, i.e., how to convert Elicit's findings into teaching materials for primary school.

In the case of pair work, it is a recognized scaffolding strategy to overcome teacher resistance or technological anxiety, a challenge identified by Garzón Patiño and Marulanda (2025) in their systematic review. For its part, the challenge of translation is highly relevant; the literature often discusses the digital divide (Arias, Castro, Forero, Della Nina Gambi, Giambruno, Pérez & Rodríguez, 2025), but its findings point to a pedagogical translation gap.

Fourth, in terms of the pedagogical applications of AI, beyond planning, teachers envisioned three possible routes for direct application in the classroom: a) project justification through the use of Elicit to justify projects and substantiate topics such as the SDGs, b) preparing materials by creating study guides or tailored digital workbooks, and c) developing teaching proposals by designing games with digital tools and role-playing games based on the reviewed literature.

These findings are an example of the leap teachers make from reviewing literature (Elicit) to creating teaching proposals (games), illustrating the transition from AI as a search tool to AI as a creative partner. This coincides with García-Peñalvo (2023), who points out that AI can be used to innovate teaching methodologies, as the participants did by connecting AI with active methodologies.

Finally, the teacher's pragmatic research (Assisted Action Research) reveals that the research carried out by teachers is not theoretical or basic, but deeply pragmatic and oriented towards immediate pedagogical action in the classroom.

In general, they do not seek to publish research, but rather to apply it. In this sense, the applications identified include: a) the rationale, where Elicit is used to justify projects and review progress for classroom projects; b) preparation, where it seeks to be up to date in order to suggest work plans to parents; and c) action, which allows academic findings to be translated into teaching materials, study guides, and teaching proposals. In this sense, the findings align directly with Schön's (1983) concept of the reflective practitioner, who argues that the most effective practitioners do not mechanically apply theories, but rather develop a process of reflection-in-action (and on-action). In the experiences, teachers are using AI tools (Elicit, Perplexity) as advanced tools to enhance this cycle of reflection; they seek literature (reflection) to inform their future practice (action).

The teachers' research model is a form of action research. As defined by Kemmis, McTaggart, and Nixon (2014), it is a participatory and situated process whose goal is not generalization, but rather the improvement of one's own practice and understanding of it. In the case of the experiences, the teachers are executing micro-cycles of Action Research: they identify a problem (need for a project), investigate (Elicit), plan (guides), and act (classroom implementation).

## CONCLUSIONS

The adoption of AI tools for research by primary school teachers was practically non-existent prior to the direct training intervention. The initial diagnosis, consistent across both private and public institutions, revealed an incipient approach and a general lack of knowledge regarding the effective integration of these technologies. However, once exposed to specific tools through workshops, teachers immediately identified their pragmatic applicability.

The predominant tools were Elicit, for searching and systematizing academic literature, and chatbots such as Perplexity, used as assistants for structuring work plans. The use of these tools is concentrated in specific phases of the teacher's research process, understood as action research: a) Grounding and diagnosis, and b) Planning and design.

In addition, two critical phases were identified that hinder the integration of AI: a) the primary barrier characterized by AI illiteracy, and b) the secondary barrier made visible by the pedagogical translation gap. A relevant finding that transcends mere digital competence is the cognitive challenge of translating academic language.

The study corroborates that the research conducted by primary school teachers is not theoretical or basic, but rather deeply pragmatic and oriented towards immediate pedagogical action. Teachers do not seek to conduct research for publication, but rather to substantiate, plan, and improve their direct classroom interventions. In this sense, recommendations for effective integration should focus on positioning AI as a tool to assist action research.

Training strategies should: a) bridge the skills gap through scaffolding methodologies, b) focus on immediate applicability, providing structured models (such as the RITA model for prompts) that facilitate the connection between the tool and the specific pedagogical need (planning, material design, project justification), and c) address the pedagogical translation gap by explicitly instructing on the use of AI not only to search for information, but also to simplify, adapt, and transform it into teaching formats.

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# Epilogue

It is no coincidence that this book ends without offering a definitive conclusion. Those who have journeyed through its pages will have noticed that, rather than answers, what is proposed here are paths, tensions, and decisions yet to come. Artificial intelligence has entered education not as just another tool, but as an actor that redefines roles, discourses, and ways of thinking about the educational experience. In this landscape, literacy can no longer be understood as a mere technical skill, but as a complex cultural practice—one deeply connected to ethics, the politics of knowledge, and the conscious exercise of teaching.

The voices gathered in this work share a common gesture: that of yielding neither to technological fascination nor to critical paralysis. Instead of treating AI as a threat or a magical solution, the authors have chosen to think about it from the perspective of pedagogical experience, context, and situated reflection. There are no recipes here, but there are compasses. And in an age of automatisms, every compass is also a form of resistance.

This book does not seek to close the debate, but to amplify it. It invites us to keep writing—but with new questions. To keep teaching—but with the awareness that the classroom, whether physical or virtual, remains a space of symbolic construction. To keep fostering literacy—but without giving up what makes us human. Perhaps that is, ultimately, the great task that this work leaves open: to embrace artificial intelligence not only as an object of knowledge, but as an opportunity to reimagine—with boldness and responsibility—what it means to educate today.

# Additional information

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