DIGITAL INNOVATIONS in Education

Brief N°4

AI Revolution in Higher Education

What you need to know

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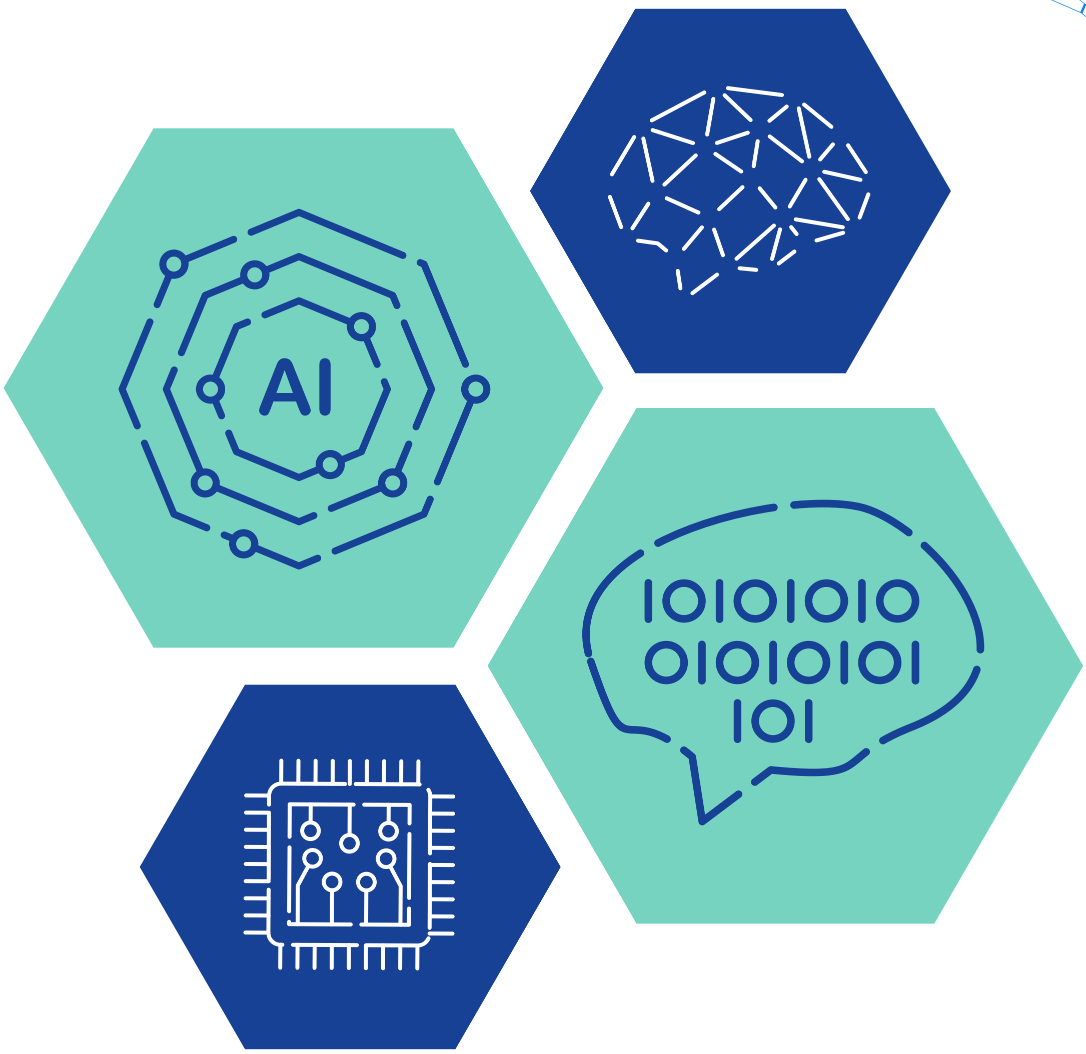

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I EXECUTIVE SUMMARY

Artificial Intelligence (AI) is revolutionizing Higher Education (HE), transforming how students learn, faculty teach, and institutions operate. Across Latin America and the Caribbean (LAC), AI-powered tools are being integrated into classrooms, research, and administrative processes, offering scalable and personalized solutions to improve educational access, efficiency, and equity. However, despite its vast potential, AI adoption in the region remains fragmented, hindered by infrastructure gaps, limited AI innovation, and challenges in faculty upskilling and talent retention.

This report examines the transformative potential of AI in HE, focusing on key applications, challenges, and strategic recommendations for ethical integration. AI tools are already making a significant impact in student support, faculty research, and institutional management. Recent studies of well-designed Generative AI systems demonstrate promising results. For instance, AI-powered assignment platforms have increased student placement efficiency by 20% and improved options for under-assigned students by 38% (Larroucau et al., 2024). New studies of carefully implemented Generative AI tools demonstrate meaningful improvements in learning outcomes - a Harvard study found students using AI tutors learned more than twice as much in less time compared to active learning classrooms (Kestin et al., 2024), while a Stanford study demonstrated how AI-enhanced tutoring could effectively scale expert teaching practices, leading tutors to employ more effective pedagogical strategies while achieving improvements at a modest cost of $20 per tutor annually (Wang et al., 2025). These technologies are helping to close learning gaps and expand access to quality education, addressing Bloom's "2 Sigma Problem" (Bloom, 1984) by offering personalized, 24/7 learning support that complements traditional teaching methods.

However, realizing AI's full potential in the LAC region requires overcoming critical barriers. These include the digital divide, which limits AI accessibility in rural areas; the low participation of Latin American institutions in global AI innovation (contributing only 0.21% of AI patents); and ethical concerns surrounding algorithmic bias and data privacy. Addressing these challenges necessitates a holistic approach—one that includes investments in AI research, faculty training programs, improved digital infrastructure, and stronger multisectoral collaboration.

The implementation landscape reveals both opportunities and significant hurdles. Faculty surveys indicate that while 61% have used AI in teaching and 65% view it as an opportunity, substantial concerns remain. Specifically, 83% worry about students' ability to critically evaluate AI outputs, and 80% say their institutions lack comprehensive AI guidelines. These findings underscore the need for robust faculty support systems and clear institutional policies. Furthermore, early evidence suggests that without careful design and implementation, AI tools may inadvertently amplify existing educational inequities, particularly affecting students from underserved communities and non-native language speakers.

The report categorizes AI applications into three primary areas: **student-centered tools**, **faculty-focused innovations**, and **institutional applications**, each of which is explored in depth. The table below provides an overview of the AI-driven innovations discussed in this report:

"AI should not be seen as a replacement for human expertise but rather as a way to enhance and scale the impact of human judgment and skills"

Key Takeaways:

- **AI can be a game-changer for higher education.** From improving learning outcomes to optimizing institutional processes, AI is driving unprecedented transformations.
- **Regional adaptation is crucial.** AI tools must align with Latin America's social, economic, and infrastructural realities to maximize impact.
- **Investment in AI innovation is needed.** The region's low contribution to AI patents signals a need for stronger research ecosystems and public-private collaboration.
- **Faculty training and retention are essential.** Without well-equipped educators, AI cannot be effectively integrated into teaching and research.
- **Addressing digital equity is non-negotiable.** Expanding broadband access and affordable AI solutions is key to ensuring all students benefit from these technologies.
- **Ethical AI governance is imperative.** AI adoption must be transparent, accountable, and bias-free to build trust and ensure equitable access.

The Path Forward

To fully harness AI's potential in higher education, Latin America must act decisively. Governments, universities, and the private sector must work together to foster an innovation-friendly environment while prioritizing digital equity, faculty development, and ethical AI governance. The future of higher education is being reshaped by AI, and the choices made today will determine whether this transformation leads to greater inclusion and learning opportunities for all.

"AI-powered assignment platforms have increased student placement efficiency by 20% and improved options for under-assigned students by 38%"

This report serves as a guide for policymakers, educators, and institutional leaders seeking to navigate the AI revolution in higher education. By taking a strategic, evidence-based approach, the LAC region can position itself at the forefront of AI-driven educational innovation.

Table 1: AI Applications in Higher Education

Category	AI Application	Impact in Higher Education
Student-Centered Tools	**Adaptive Learning & AI Tutors**	Enhances personalized learning, provides real-time feedback, and reduces learning gaps.
Faculty-Focused Innovations	**AI in Assessment & Evaluation**	Streamlines grading, ensures fairness, and provides data-driven feedback for students.
	AI-Powered Research Assistance	Accelerates literature reviews, automates citation analysis, and enhances interdisciplinary research.
Institutional Applications	**AI in Institutional Decision-Making**	Supports resource allocation, predicts enrollment trends, and enhances financial planning.
	AI-Driven Student Support & Profiling	Identifies at-risk students, predicts academic performance, and enables early interventions.
	AI-Powered Admissions & Enrollment Systems	Optimizes student placement, reduces administrative bottlenecks, and improves institutional efficiency.
	Ethical & Regulatory AI Frameworks	Ensures algorithmic transparency, promotes responsible AI adoption, and safeguards student privacy.

II INTRODUCTION

In a global context where Higher Education (HE) massification faces increasing demands for quality and transparency, institutions are adopting advanced technologies, such as AI tools, with the promise of transforming their practices and meeting these challenges. Higher Education in Latin America and the Caribbean has expanded significantly, growing from 7.4 million students in 1990 to 15 million in 2004 (Fernández, 2007). This growth accelerated further, with enrollments increasing from 21 million in 2009 to more than 31 million in 2023, reflecting a near 100% rise over two decades. Brazil, Mexico, Argentina, and Colombia alone account for 21 million students, representing 68% of the total in the region (UNESCO UIS, 2024).

The number of universities in Latin America has grown significantly since the mid-20th century, rising from 75 in 1950 to an estimated 1,867 today, representing 13% of the global total of Higher Education Institutions (HEIs) (Fernández, 2007; UniRank, 2024). Alongside this expansion, Technical and Professional Education (TPE) has become a critical component of the region's educational landscape, with an estimated 5 million students enrolled[1][2], accounting for 17% of total HE enrollment according to UNESCO UIS (2024). As noted by Sevilla (2017) in the CEPAL report *Panorama de la Educación Técnica Profesional en América Latina y el Caribe*, participation in TPE has shown notable trends, particularly in contexts where technical offerings are predominantly mixed or private, highlighting its importance in diversifying educational pathways and addressing regional labor market demands.

Despite the massification of HE in Latin America and the Caribbean, significant gaps in access and quality persist. According to Ferreyra et al. (2017), students from the lowest quintiles represented only 24% of total enrollment in 2012, showing improvement from 16% in 2000 but still reflecting structural inequalities. Furthermore, these students tend to concentrate in less rigorous institutions or low-quality programs, limiting their potential to achieve the same economic benefits as their higher-income peers. The rapid expansion of the system has also raised questions about institutions' ability to maintain quality standards, particularly in a context where the growth of private institutions presents unique challenges and opportunities for balancing accessibility with effective learning outcomes.

Financing HE has been key to expanding access, but it also presents challenges such as accumulated debt and inequality in the academic progression of lower-income students. Policies like student loans and subsidies have enabled low-income students to access HE but have also increased debt levels among graduates, raising concerns about the financial sustainability of the model (Ferreyra et al., 2017). At the same time, the impact on social mobility has been significant but uneven (INACAP, 2023). Students from low-income families are less likely to complete their studies due to barriers such as inadequate academic preparation and the need to combine studies with work. These structural inequalities limit HE's potential to act as a true engine of social mobility in the region, a role that has proven particularly valuable in the technical and professional world (CAF, 2018; Arias Ortiz et al., 2021).

1 This figure contrasts with data from UNESCO UIS, which reports nearly 2.7 million students enrolled in tertiary education programs at ISCED level 5, typically associated with technical or professional education. Notably, ISCED level 6 also includes some technical programs lasting four years, such as those found in Chile's technical or professional education system, further complicating the categorization.

2 The estimate of 5 million TPE students was calculated by multiplying the total student enrollment in UNESCO UIS (2024) by the estimated percentage of participation in technical education in Latin America and the Caribbean, based on Sevilla's (2017) analysis in the CEPAL report.

TIMSS and PIAAC results reveal low learning outcomes and major educational challenges. In the PIAAC assessment (table 2), designed to measure skills in reading, mathematics, and problem-solving in digital environments, countries like Perú, Chile, México, and Ecuador show that the majority of their adult populations perform at basic or lower levels in these areas. On the other hand, only 7% and 5% of the populations in Perú and Ecuador, respectively, reached advanced levels in problem-solving in digital environments (OECD, 2020; OECD, 2024). This presents significant challenges as the development of various digital technologies continues to impact labor markets and HEIs.

Table 2: PIAAC results.

Country	Literacy Store	Numeracy Score	Literacy Level	Numeracy Level	Problem-Solving in Digital Environments	Year
Chile	218	214	Majority level 1 or 2	Nivel 1 o inferior	15% at Level 2 or 3	2023
México	222	210	Majority level 1 or 2	Majority level 1 or 2	10% at Level 2 or 3	2018
Perú	196	178	Majority Level 1 or less	Majority Level 1 or less	7% at Level 2 or 3	2018
Ecuador	196	185	Majority Level 1 or less	Majority Level 1 or less	5% at Level 2 or 3	2018
United States	272	257	Majority Levels 2 and 3	Majority Levels 2 and 3	29% at level 2 or 3	2018
OECD	266	262	Majority Levels 2 and 3	Majority Levels 2 and 3	30% at Level 2 or 3	-

Note: Mean proficiency scores of 16-65 year-olds in literacy and numeracy, and the percentage of 16-65 year-olds scoring at Level 2 or 3 in problem solving in a technology-rich environment.

The results of TIMSS 2023 confirm the educational lag in Latin America. With eighth-grade students in Brazil scoring 378 points in mathematics and 420 points in science, while Chile achieved 416 and 455 points, respectively, both far below the international averages of 478 and 485 points (IEA, 2024) (table 3). These scores underscore the persistent inequities in education systems across the region. In contrast, the implementation of Digital Personalized Learning (DPL) in Kenya demonstrates the potential of AI-driven tools to address such gaps. The study found that the use of DPL in pre-primary classrooms led to a statistically significant improvement in learning outcomes, with an effect size of 0.53 standard deviations (SD) overall, and specific gains of 0.45 SD in numeracy and 0.45 SD in literacy (Major et al., 2024). These results highlight how AI-powered tools, when integrated effectively into classrooms, can enhance learning outcomes and help bridge educational inequities, offering a promising pathway for regions struggling to meet global standards.

> **"Nearly half of enrolled students in LAC do not complete their degree by age 29, with about 50% dropping out during their first year"**

Table 3: Average scores in Mathematics and Science for 4th and 8th grade students based on TIMSS 2023 results.

Country	Math (Grade 4)	Math (Grade 8)	Science (Grade 4)	Science (Grade 8)
Brazil	400	378	425	420
Chile	444	416	479	455
United States	517	488	532	513

AI can potentially transform education by personalizing learning and improving efficiency. The integration of AI holds tremendous promise for educational systems, offering the ability to close learning gaps, streamline administrative processes, and enhance academic performance. These technologies not only improve efficiency but also enable personalized instruction tailored to each learner's unique needs, helping to address persistent challenges such as low student engagement and uneven educational outcomes.

However, many developing regions struggle with the infrastructure needed to support AI in education. Despite AI's potential, foundational infrastructure issues persist, particularly in rural and remote areas where reliable internet access is scarce. Distributing tablets and computers alone does little to alleviate learning barriers if connectivity and long-term maintenance are lacking (ILIA, 2024, pag. 44). Addressing these gaps requires holistic digital inclusion strategies, including robust training for educators and students and sustainable funding models.

Faculty members see AI as both an opportunity and a challenge. The 2025 Digital Education Council Global AI Faculty Survey of 1,681 faculty members across 52 institutions revealed that while 61% have used AI in teaching and 65% view it as an opportunity, significant concerns remain. 83% worry about students' ability to critically evaluate AI outputs, and 80% say their institutions lack comprehensive AI guidelines. Faculty responses indicate that increased access to AI tools and expanded training on AI literacy and skills are critical enablers of adoption (Digital Education Council, 2025).

Understanding these faculty perspectives requires considering AI's long technological evolution. Beginning with Alan Turing's pioneering "Turing Test" (Turing, 1950), key milestones include Rosenblatt's perceptron in 1958, IBM Deep Blue's victory over Garry Kasparov in 1997 (Campbell et al., 2002), AlexNet's revolution in neural networks in 2012 (Krizhevsky et al., 2012), and AlphaGo's triumph over the world Go champion in 2017 (Silver et al., 2017). Recent developments in large language models like ChatGPT (2022) and DeepSeek R1 (2024) have accelerated AI adoption across sectors, exemplified by the California State University system becoming the world's largest AI-powered university network in 2025 [3]. As LLM development becomes more cost-efficient (DeepSeek-AI, 2024), new applications continue emerging to address educational challenges like Bloom's 2 Sigma–enhancing personalized learning at scale– (Bloom, 1984) while reinforcing academic integrity through advanced monitoring mechanisms.

3 In February 2025, the CSU became the largest deployment of ChatGPT integrated among students, faculty, and staff. https://openai.com/index/openai-and-the-csu-system/

AI TIMELINE

1950
Alan Turing published "Computing Machinery and Intelligence," introducing the Turing test and opening the doors to what would be known as AI.

1956
John McCarthy, Marvin Minsky, Nathaniel Rochester and Claude Shannon coined the term artificial intelligence in a proposal for a workshop widely recognized as a founding event in the AI field.

1964
Daniel Bobrow developed STUDENT, an early natural language processing (NLP) program designed to solve algebra word problems, while he was a doctoral candidate at MIT.

1966
Joseph Weizenbaum created Eliza, one of the more celebrated computer programs of all time, capable of engaging in conversations with humans and making them believe the software had humanlike emotions.

1968
Terry Winograd created SHRDLU, the first multimodal AI that could manipulate and reason out a world of blocks according to instructions from a user.

1997
Sepp Hochreiter and Jürgen Schmidhuber proposed the Long Short-Term Memory recurrent neural network, which could process entire sequences of data such as speech or video.

2000
University of Montreal researchers published "A Neural Probabilistic Language Model," which suggested a method to model language using feedforward neural networks.

2006
Fei-Fei Li started working on the ImageNet visual database, introduced in 2009, which became a catalyst for the AI boom and the basis of an annual competition for image recognition algorithms.

2009
Rajat Raina, Anand Madhavan and Andrew Ng published "Large-Scale Deep Unsupervised Learning Using Graphics Processors," presenting the idea of using GPUs to train large neural networks.

2011
Jürgen Schmidhuber, Dan Claudiu Cireşan, Ueli Meier and Jonathan Masci developed the first CNN to achieve "superhuman" performance by winning the German Traffic Sign Recognition competition.

2012
Geoffrey Hinton, Ilya Sutskever and Alex Krizhevsky introduced a deep CNN architecture that won the ImageNet challenge and triggered the explosion of deep learning research and implementation.

2016
DeepMind's AlphaGo defeated top Go player Lee Sedol in Seoul, South Korea, drawing comparisons to the Kasparov chess match with Deep Blue nearly 20 years earlier.

2017
Stanford researchers published work on diffusion models in the paper "Deep Unsupervised Learning Using Nonequilibrium Thermodynamics." The technique provides a way to reverse-engineer the process of adding noise to a final image.

2019
Microsoft launched the Turing Natural Language Generation generative language model with 17 billion parameters.

2020
The University of Oxford developed an AI test called Curial to rapidly identify COVID-19 in emergency room patients.

2021
The University of California, San Diego, created a four-legged soft robot that functioned on pressurized air instead of electronics.

2022
OpenAI released ChatGPT on Nov. 30 to provide a chat-based interface to its GPT-3.5 LLM, signaling the democratization of AI for the masses.

2023
OpenAI announced the GPT-4 multimodal LLM that processes both text and image prompts. Microsoft integrated ChatGPT into its search engine Bing, and Google released its GPT chatbot Bard.

2024
Generative AI tools continued to evolve rapidly with improved model architectures, efficiency gains and better training data.

2025
Corporate spending on generative AI is expected to surpass $1 trillion in the coming years. Bloomberg predicts that GenAI products "could add about $280 billion in new software revenue driven by specialized assistants, new infrastructure products and copilots that accelerate coding."

These technological advances are already showing concrete impact in educational settings. In Chile, AI is already being applied to tackle structural challenges in education, demonstrating its potential to improve equity and efficiency in access to HE. The admissions process in Chile is partially centralized, where students apply to universities through a unified platform managed by the Ministry of Education. However, this system only includes a subset of institutions, as many private universities and technical institutes operate outside the centralized framework, offering programs independently. This dual structure complicates the selection process, contributing to inefficiencies such as nearly 40% of students not selecting their first-choice program and between 5% and 10% missing opportunities to enroll in programs that could significantly enhance their academic and professional prospects (Kapor, Karnani, & Neilson, 2022). These inefficiencies highlight the pressing need for innovative tools and new policy approaches to address systemic barriers in the admissions process.

To mitigate these challenges, a centralized assignment system leveraging advanced AI algorithms was introduced. This system utilizes a deferred acceptance algorithm with tie-breaking rules to optimize student preferences and school priorities. As a result, the percentage of students not selecting their first-choice programs decreased by 20%, and placement outcomes for poorly matched students improved by 38% (Larroucau et al., 2024). These results illustrate one tangible way in which AI can contribute to more inclusive and effective educational systems while emphasizing the importance of transparent implementation to maximize its impact and build trust among stakeholders.

Objectives. This report aims to explore the current state and transformative potential of AI in higher education across Latin America and the Caribbean (LAC). While AI offers promising solutions, it is not a panacea for educational challenges—rather, it can be effective when thoughtfully applied to specific, well-defined problems. It is essential to emphasize that AI should not be seen as a replacement for human expertise but rather as a complementary tool to enhance and scale educational impact when deployed strategically.

The guide examines current AI applications across three key stakeholder groups: For **students**, we explore how AI enables personalized learning experiences through adaptive systems and AI tutoring; for **faculty**, we analyze how AI can streamline administrative tasks, enhance teaching practices, and support research activities; and for **administrators**, we investigate how AI can optimize institutional operations through improved resource allocation and data-driven decision-making. Through this analysis, we aim to help education systems and HEIs make informed decisions about where and how to integrate AI effectively, identifying specific use cases where it can have meaningful impact while acknowledging its limitations and the continued importance of human judgment in education.

This guide (Brief N°4, 2025) is part of the ***Digital Innovations in Education*** brief series, which aims to provide insights into ways to improve the digitalization of education in the Latin America and Caribbean (LAC) region, with a focus on innovations that enhance learning outcomes. By showcasing actual cases from LAC countries and highlighting successful implementations and best practices, this series supports the World Bank and Inter-American Development Bank's strategic partnership to accelerate the digital transformation of education systems in the region.

Readers can also explore the companion briefs in this series:

AI Revolution in Education (Brief N°1, 2024): Provides a broad overview of AI's transformative potential in education

Transforming Education in Uruguay through Technology (Brief N°2, 2024): Examines Uruguay's pioneering experience in educational technology integration

100 Students' Voices on AI in Education (Brief N°3, 2024): Offers insights from student perspectives on AI implementation in education

You can find more about the series and access previous briefs here.

III Methodology

Methodological Guide. To develop this practical guide on Artificial Intelligence in HE, a mixed-methods approach was employed, combining literature review, testing the AI tools, and case studies from global and regional contexts.

An initial pool of 438 AI tools was identified through Edtech Insiders, a platform offering one of the most comprehensive repositories of educational tools. From this pool, the World Bank team added 34 AI tools and conducted an internal selection process to identify 20 tools that stood out due to relevant evidence or well-recognized use cases. These tools were categorized into five key areas: **Adaptive learning** (systems that adjust content, pace, and feedback in real-time to individual student needs), **intelligent assessment** (automated tools for evaluating student performance), **administrative tools** (including student profiling and prediction systems, chatbots as well as AI systems to streamline institutional operations), **research facilitation** (platforms aiding academic research), and **ethical and regulatory frameworks**.

Additionally, a comparative review of international and regional regulatory frameworks highlighted gaps in areas like data protection, algorithmic transparency, and ethical AI usage, emphasizing the need for context-specific regulatory strategies in Latin America. This structured methodology ensures the guide is evidence-based and practical for advancing AI adoption in higher education.

Access to information remains a challenge, as some data on "in-house" tools developed by higher education institutions (HEIs) are unpublished or restricted. Additionally, there is a lack of empirical evidence in Latin America, where many promising initiatives are still in early stages or lack rigorous evaluations to assess their impact. Moreover, the rapid pace of technological advancements poses challenges for institutions in staying updated and effectively integrating new tools into existing systems.

IV. Overview of AI Tools in Higher Education

This guide on AI in HE is organized into five categories and twenty AI-driven tools tailored to benefit students, faculty, and administrative staff. For students, it highlights tools like adaptive learning systems and AI tutoring systems. Faculty-focused tools include automated assessment tools, personalized feedback systems, and research support platforms to enhance teaching and knowledge generation. For administrators, it features tools for institutional management and data-driven decision-making, such as resource planning, AI-powered chatbots and predictive analytics to identify at-risk students. The guide also addresses key ethical and operational challenges, including algorithmic transparency, sustainable funding, and evidence of AI's effectiveness in improving learning and institutional efficiency.

III STUDENTS-CENTERED TOOLS

A. AI Tutoring Systems and Adaptive Learning

AI-powered student-centered tools in higher education leverage advanced technologies to enhance learning outcomes and provide personalized educational experiences. Among these tools, AI Tutoring Systems (AITS) and Adaptive learning platforms represent key innovations that use AI to personalize education by adapting content, pace, and feedback in real-time to meet each learner's needs. Defined by Du Plooy et al. (2024) as a technology-driven pedagogy, these systems utilize tools like pre-knowledge quizzes, learning management platforms (e.g., Moodle, Connect LearnSmart), and adaptive algorithms to create customized pathways. Before Generative AI, these advancements had led to significant academic improvements in 59% of studies and increased engagement in 36%, highlighting their transformative impact on learning.

The integration of Generative AI offers potential for even greater impact, though implementation details prove critical. While earlier meta-analyses found modest but significant positive effects of digital platforms (g = 0.278) (Alshammary and Alhalafawy 2023), the evidence we will present demonstrates that well-designed AI systems can achieve dramatically stronger results in higher education settings. However, these outcomes depend heavily on thoughtful implementation and careful attention to design principles, as both the potential benefits and risks of these systems have grown with their increased capabilities.

AI Tutoring Systems (AITS).

Research increasingly demonstrates that well-designed AI tutoring systems can significantly enhance learning outcomes in higher education, though much of our understanding also draws from K-12 and other educational contexts. While research specifically focused on higher education applications is still emerging, evidence across educational levels provides valuable insights into both the potential and limitations of AI tutoring systems, helping inform their development and implementation in university settings.

> **"Well-designed AI tutoring systems can significantly enhance learning outcomes in higher education... students using AI tutors learned more than twice as much in less time"**

Early evidence from higher education settings shows promising results. A 2024 Harvard study involving 194 undergraduate physics students represents one of the few rigorous evaluations of AI tutoring effectiveness in higher education. The study found that participants using AI tutors learned more than twice as much in less time compared to those in active learning classrooms, with 83% of students rating AI explanations as comparable to or better than human instructors. The research identified several critical design principles for effective AI tutoring systems, including facilitating active learning, managing cognitive load, promoting growth mindset, providing scaffolded content, ensuring accuracy, delivering timely personalized support, and enabling self-paced learning (**Kestin et al., 2024**).

A similar result is found at Universitas Muhammadiyah Muara Bungo. The study found that students using AI tutoring achieved significantly higher mean scores (81.81) compared to the control group (70.45). The study highlighted the importance of enhanced student engagement, interaction with learning materials, and peer collaboration as key factors contributing to improved performance (Hakiki et al, 2023).

However, research also reveals important challenges in how students interact with AI systems. A 2024 study of 38 university ESL learners conducted a detailed comparison of help-seeking behaviors between students using AI tutors versus human experts. The research found that students using AI tutors often skipped critical learning steps, requested direct answers rather than guidance, and failed to evaluate AI-provided help critically. In contrast, students working with human experts followed a more structured learning process, asked for hints rather than solutions, and carefully evaluated feedback before implementing it (Chen et al, 2025). Supporting these findings, another study of 666 participants examining the relationship between AI tool use and cognitive skills revealed concerning correlations. The research found strong negative correlations between AI tool use and critical thinking abilities, alongside a strong positive correlation with cognitive offloading, suggesting that increased reliance on AI tools may lead to decreased independent problem-solving capabilities (Gerlich, 2025).

Design and implementation prove critical to the success of AI tutoring systems. This growing body of evidence suggests that AI tutoring systems' effectiveness depends critically on their design and implementation. Bastani et al. (2024) conducted a field experiment with nearly a thousand high school students, comparing two different GPT-based tutoring approaches. While a basic GPT integration showed initial performance improvements of 48%, students performed 17% worse than the control group when AI support was removed. However, a carefully designed "GPT Tutor" with specific learning safeguards achieved a 127% improvement in performance while largely mitigating negative learning effects. These findings underscore the importance of thoughtful system design that promotes active learning and prevents overreliance on AI assistance.

Well-designed systems can overcome these challenges through thoughtful implementation. Recent evidence from a Stanford study demonstrates how thoughtfully designed AI tutoring systems can overcome these challenges. Wang et al. (2025) conducted the first randomized controlled trial of a Human-AI tutoring system involving 900 tutors and 1,800 K-12 students. Their Tutor CoPilot system represents a novel approach that leverages models of expert thinking to provide real-time guidance to tutors. The study found that students working with AI-supported tutors showed a 4 percentage point increase in topic mastery, with even larger gains (9 percentage points) observed among students working with less experienced tutors. Through analysis of over 550,000 messages, the researchers found that tutors with AI support were more likely to use strategies that fostered deeper understanding, such as asking guiding questions rather than providing direct answers. Importantly, this improvement was achieved at a modest cost of approximately $20 per tutor annually.

Recent evidence from developing contexts further reinforces the potential of AI tutoring systems and provides insights for institutional implementation. While focused on secondary education, a 2024 randomized controlled trial in Nigeria offers valuable lessons for higher education settings. The study evaluated an after-school program that used generative AI (Copilot Chat) as a virtual tutor and after six weeks of implementation achieved remarkable learning gains of 0.3 standard deviations - equivalent to nearly two years of typical learning progress. This placed the intervention's effectiveness above 80% of other educational interventions studied through RCTs in developing countries. The benefits extended beyond the targeted English language skills to improve performance across subjects in students' regular curriculum, demonstrating how thoughtfully implemented AI tutoring can enhance broader learning capabilities and complement existing institutional practices. Girls –initially lagging behind boys–showed even greater gains, indicating the program's potential to bridge gender gaps in learning (De Simone et al., forthcoming).

Understanding these principles paves the way for effective institutional implementation. This evidence, while drawn from various educational contexts, provides crucial insights for higher education implementation. Jill Watson, Cogniti, and Chile's Mateo are additional examples that demonstrate how these principles are being applied in practice. Their implementation underscores the importance of context-aware AI tools that enhance learning outcomes, optimize student engagement, and complement existing instructional methodologies.

Jill Watson, developed at Georgia Tech and powered by ChatGPT, exemplifies how AITS can enhance learning by offering personalized and efficient academic support. This tool serves students with real-time, context-aware responses to domain-specific queries, with an average response time of 6.8 seconds. A recent evaluation involving 150 questions showed Jill Watson achieving a 76.7% success rate, outperforming other AI systems like Legacy Jill Watson (26.0%) and OpenAI Assist (31.3%) (Figure 5). Furthermore, Jill Watson minimizes harmful outputs (5.7% failure rate) and effectively mitigates confusion caused by retrieval issues, positioning it as a reliable tool for enhancing student learning outcomes (Taneja et al., 2024).

This innovation addresses one of the key challenges in online education: the lack of teaching presence, which often results in lower engagement and academic performance. Leveraging retrieval-augmented generation (RAG), Jill Watson ensures accurate, context-aware responses grounded in instructor-approved materials, effectively reducing hallucinations common in large language models. Deployed across institutions and serving over 1,300 students, Jill Watson has demonstrated its ability to improve outcomes, with users achieving higher A grades (66.2% vs. 62.3%) and fewer C grades (3.0% vs. 7.4%) compared to non-users. These results highlight its potential to bridge the gap between online and in-person learning while enhancing engagement and academic success (Kakar et al., 2024).

Figure 3. Jill Waston and the Q&A on general syllabus and schedule.

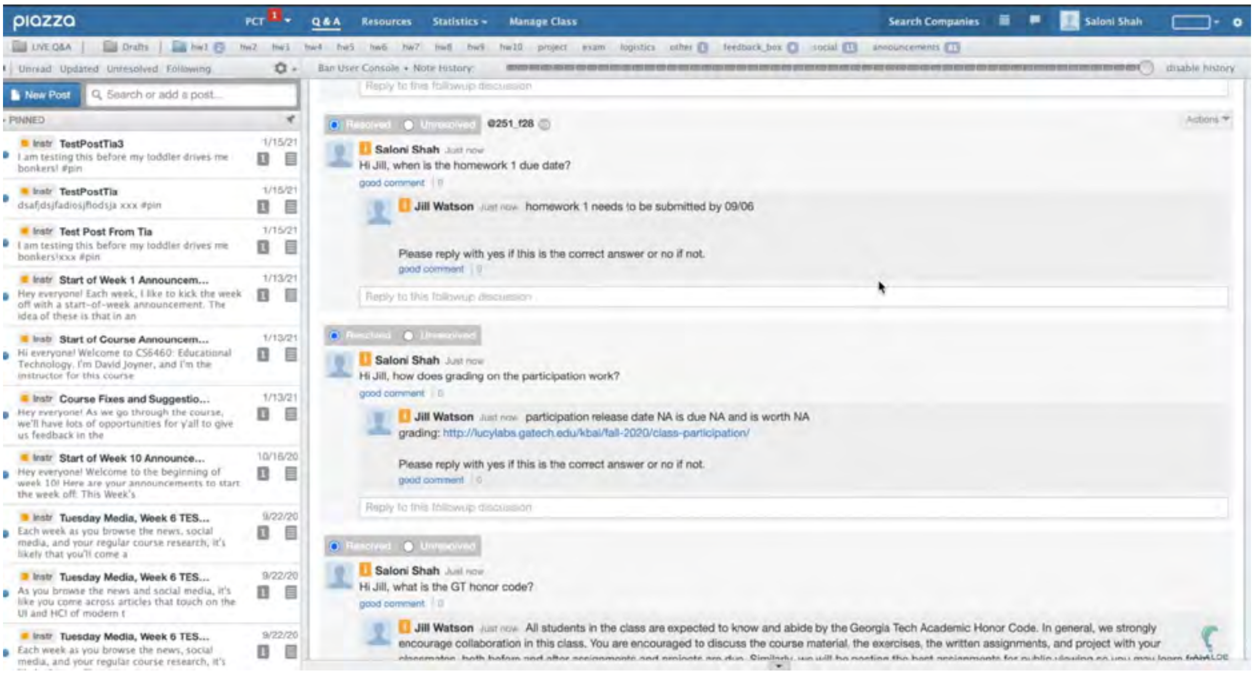


Figure 4.Integration of chat GPT for PersonalAI Teaching Assistant.

Figure 5. Jill Watson and chatGPT 3.5 answers to students' questions. Extracted from (Kakar et al., 2024).

Question: How does Thagard explain the concept of 'free will' within the frameworks he discusses in his book "MIND: Introduction to Cognitive Science"?
Jill Watson: Thagard does not explicitly discuss the concept of "free will" within the frameworks he discusses in his book "MIND: Introduction to Cognitive Science." The book primarily focuses on explaining various aspects of intelligent behavior and the different approaches to modeling the mind. Thagard's emphasis is on understanding the nature of the mind and the cognitive processes that underlie intelligent behavior, rather than delving into philosophical concepts such as free will.
ChatGPT 3.5: In his book "MIND: Introduction to Cognitive Science," Thagard addresses the concept of free will within the context of cognitive science, exploring how cognitive processes give rise to our sense of agency and decision-making. Thagard's approach to free will in "MIND" is consistent with his broader views on consciousness and cognition, emphasizing the role of neural mechanisms and computational processes in shaping human behavior. While "MIND" covers a wide range of topics in cognitive science, including perception, language, and reasoning, Thagard's discussion of free will typically focuses on the following key points: [...]

Cogniti is a flexible solution powered by ChatGPT[4] designed to directly benefit students through personalized and adaptive learning experiences. While educators are responsible for creating and tailoring the Intelligent Tutoring Systems (ITS) to meet the specific needs of their courses, it is the students who are the ultimate beneficiaries and end-users of these tools. Cogniti enables the customization of learning in disciplines such as biology, psychology, and journalism, ensuring that each student receives targeted support based on their progress and areas for improvement.

According to the Cogniti Mini-Symposium (2024), implementations across HEIs have showcased its effectiveness. For example, at the University of Sydney, Cogniti-powered AI agents were used in a microbiology course to facilitate personalized short-answer practice for over 800 students, generating 1,200 interactions midway through the semester and identifying real-time knowledge gaps. In chemistry tutorials, Cogniti reduced incorrect answers by 90% and increased student confidence in peer discussions by 86%. Additionally, Cogniti supports role-play scenarios such as newsroom simulations for journalism students, enhancing skills in court reporting and media law. This scalable and versatile platform fosters engagement, boosts confidence, and improves learning outcomes through data-driven teaching strategies.

Tutoring systems of any form have consistently demonstrated their impact on academic success. Yana-Salluca et al. (2024) highlight how personalized tutoring transforms academic performance in HE by closing learning gaps and strengthening key skills. Cooper (2010) emphasizes that in-person tutoring centers boost retention and graduation rates through group sessions and access to academic resources. During the COVID-19 era, Hardt et al. (2023) reported that remote tutoring led to a 30% increase in credits earned and reduced academic inequalities. Complementing this, a meta-analysis by Tlili et al. (2023) shows that ITS have a moderate impact on knowledge acquisition (g = 0.57), reaffirming the role of technology as a key ally in HE.

In Latin America, tools like the AI Tutor Mateo, developed by the Universidad Austral de Chile, exemplify the region's efforts to leverage AITS in education. Supported by Fondecyt (The National Fund for Scientific and Technological Development, Chile), Mateo focuses on leveling foundational pre-algebra mathematics skills for engineering students, offering real-time feedback and personalized learning experiences. Using mathematical expression evaluation and pattern recognition, the system provides immediate feedback on the correctness of students' work. It builds a dynamic student model through Bayesian Knowledge Tracing (BKT), a probabilistic method that estimates mastery of specific skills by analyzing sequences of correct and incorrect answers. This model enables Mateo to tailor instruction effectively by selecting exercises within the student's Zone of Proximal Development, ensuring tasks are appropriately challenging to optimize learning outcomes.

4 https://educational-innovation.sydney.edu.au/teaching@sydney/leveraging-ai-for-enhanced-financial-analysis-a-case-study-with-gpt-4-through-cogniti/

Currently in its validation phase, Mateo has been piloted in remedial courses, showcasing its potential to address academic gaps. The system also incorporates a shared control mechanism, allowing students to participate in exercise selection, which enhances motivation and engagement. Additionally, it offers a hint system to assist students when they struggle, combining general guidance and error-specific support. While evidence of its long-term impact is still emerging, Mateo's integration into academic settings demonstrates its promise in improving educational outcomes.

AI-powered Adaptive Learning Platforms

Adaptive learning platforms, such as Yellowdig and PackBack, provide personalized educational experiences by adjusting content and feedback based on students' progress and individual needs. These tools leverage artificial intelligence techniques, such as natural language processing and machine learning, to foster interaction, collaboration, and critical thinking. According to the study by Daganzo et al. (2025), students perceive that these platforms enhance their motivation and academic engagement by offering personalized content and immediate feedback. Additionally, the same study found that their use facilitates the understanding of complex concepts and the development of problem-solving skills, leading to improved academic performance. This reinforces the importance of careful implementation of these systems to maximize their positive impact on learning.

PackBack, built on Bloom's Taxonomy, serves both students and faculty by using machine learning techniques and rule-based systems to promote critical thinking skills such as analysis and evaluation. Recent evidence shows a positive correlation between its use and improved academic performance (Zangla & Walton, 2023). A study across 10 institutions and over 1,000 students revealed significant improvements in engagement, discussion quality, and academic outcomes compared to traditional LMS discussion boards. Students using PackBack posted up to 1.83 times more frequently, wrote posts with higher word counts, and included citations at twice the rate of the control group. Additionally, they achieved higher grades, with fewer earning Ds or Fs. Faculty reported increased satisfaction, citing reduced administrative burdens and deeper student engagement (Packback, 2021).

Yellowdig, on the other hand, promotes connected learning communities and student collaboration. Yellowdig serves both students (primarily user) and faculties, leveraging Natural Language Processing (NLP) and machine learning to support connected learning communities and foster student collaboration. One notable feature, Conversation Insights, employs AI to analyze text-based interactions and identify potentially harmful or inappropriate content, assigning probability scores (0-100) across categories like toxicity, obscene language, and identity attacks. This feature aims to maintain a safe and inclusive learning environment, promoting equitable participation and constructive dialogue among students.

"Without careful design and implementation, AI tools may inadvertently amplify existing educational inequities"

Studies on Yellowdig's implementation suggest its potential to enhance student engagement. Savvides et al. (2019) observed meaningful increases in community building and participation at Arizona State University (ASU) as students actively collaborated with one another. Correlations between Yellowdig participation and course grade outcomes ranged between 0.2 and 0.4, with participation predicting up to 30% of the variability in grades in communities that adhered to best practices. Mills & Laubepin (2022) argue that providing students with autonomy in role-playing simulations led to deeper engagement. Students who selected their roles achieved approximately 13.8% more participation points and wrote 35.4% longer, more reflective posts compared to peers assigned roles at random. These findings underscore the value of AI-powered tools like Yellowdig in enhancing student-centered learning strategies, yet further research is necessary to validate these results across broader contexts and diverse populations.

Figure 1. YellowDig and responsive app services.

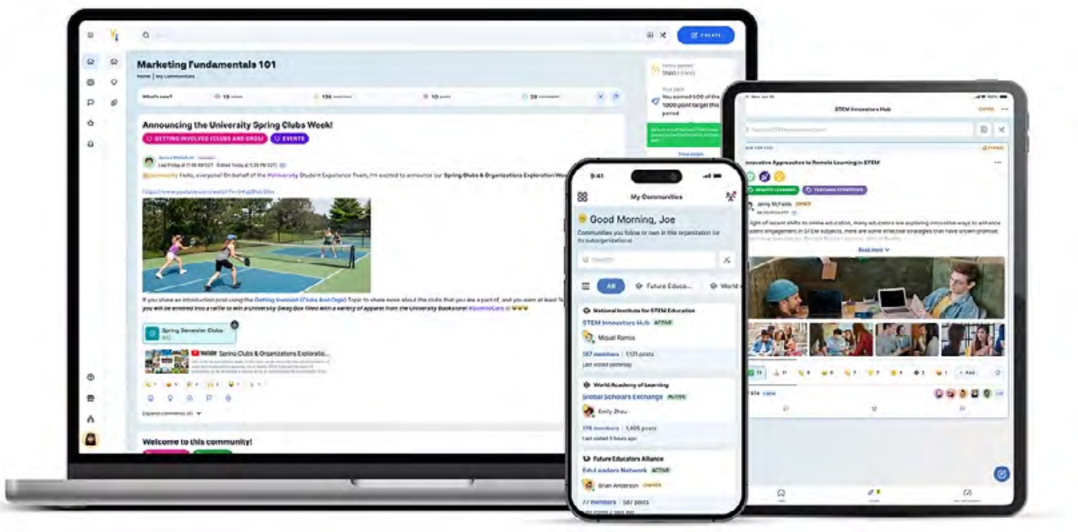


Figure 2. YellowDig Conversation Insights features.

IV FACULTY-CENTERED TOOLS AND PRACTICES

Faculty-centered tools in HE can greatly benefit from the integration of AI to streamline instructional practices, enhance teaching effectiveness, and foster innovative assignment design. As AI becomes more prevalent, faculty are challenged to be more creative and intentional in their teaching strategies. They must not only equip students with AI skills but also craft assignments that assess students' independent thinking and problem-solving abilities, beyond AI's reach. This dual challenge pushes educators to rethink traditional assessment methods and encourages the design of tasks that showcase students' original, AI-unaided work.

The growing recognition of AI's potential in education is evident, as 86% of faculty see themselves using AI in teaching in the future, and 66% believe incorporating AI is necessary to prepare students for future job markets (Digital Education Council, 2025). However, the evolving role of AI also brings challenges, with 54% of educators acknowledging the need for significant changes to student evaluation methods to maintain academic integrity. This highlights the complexity of integrating AI while ensuring assessments accurately reflect students' independent learning and skills.

AI can act as a "force multiplier" by enabling faculty to implement evidence-based teaching strategies that would otherwise be too time-consuming or resource-intensive. According to Mollick & Mollick (2023), AI supports teaching by generating multiple examples to explain complex concepts, providing varied explanations that address student misconceptions, and offering frequent low-stakes testing opportunities– all research-backed practices that are challenging to implement at scale without technological support.

To achieve this, faculty-centered tools in higher education utilize AI to streamline responsibilities, enhance instructional practices, and amplify faculty presence in the classroom. Platforms like Research Rabbit and Elicit exemplify this potential: Research Rabbit employs graph-based AI to map connections in literature, fostering interdisciplinary insights, while Elicit leverages language models to synthesize research findings and streamline literature review processes. These tools not only boost academic productivity but also enable educators to focus more on personalized teaching and student engagement.

B. AI Power Assessment and Evaluation

AI power assessment and evaluation tools are a cornerstone of faculty-centered AI tools in HE, offering a dual benefit of upholding academic integrity and enriching the student learning experience. These tools go beyond safeguarding academic standards; they actively enhance learning by delivering timely, personalized feedback that empowers students to track their progress and identify areas for improvement. For example, Cadmus, developed at the University of Melbourne, serves both faculty (primary users) and students by integrating learning analytics and scaffolded support to provide a holistic assessment experience.

Intelligent Assessment Platform. Cadmus stands out as an intelligent assessment platform that enhances evaluation practices in HE by integrating real-time analytics and providing scaffolded support. Designed as a cloud-based editor embedded in LMS, Cadmus enhances learning outcomes by offering privacy-conscious assessment experiences. A study conducted at Charles Sturt University highlighted Cadmus's potential, with 92% of students utilizing feedback features and 52% accessing embedded resources during assessments. The analysis revealed that reviewing prior feedback significantly predicted higher performance in subsequent tasks, emphasizing the importance of reflection for academic success (Hicks et al., 2021).

AI-powered online grading platform. Gradescope, an AI-powered online grading platform implemented at Stanford University, which serves both faculties (primary user) and students to enhance assessment processes by supporting handwritten, bubble sheet, online, and programming assignments. Leveraging features like handwriting recognition and dynamic rubrics, the platform ensures efficient, fair, and consistent grading while significantly reducing administrative workload. Its impact extends beyond efficiency, as evidenced by a reduction in drop/fail/withdraw (DFW) rates—dropping from 8% to 3%-4% in Business Statistics and from 39% to 24% in Organic Chemistry courses—and improved average grades, with increases of up to 23% in Business Statistics courses (from an average of 74 to 91). By streamlining feedback delivery and promoting academic integrity through tools like code similarity detection, Gradescope enhances both educator effectiveness and student learning outcomes (Hansel et al., 2024) .

Evidence from the use of an AI-based grading system using NLP and ML models like BERT achieved 91.5% accuracy, closely matching human evaluators in open-book exams, with a grading variance under 5%. The system reduced grading time by 70%, processing 1,000 open-ended responses in under 2 hours compared to 6 hours manually. Additionally, 83% of students found the feedback detailed and actionable, enhancing their understanding of academic strengths and weaknesses. These findings highlight how AI tools improve scalability, accountability, and academic engagement (Dimari et al., 2024).

However, it's important to note that while AI can support assessment, it should complement rather than replace human judgment. As emphasized in recent research, AI tools should be thoughtfully integrated into teaching practices with clear pedagogical goals in mind, rather than being deployed simply because they are available. Faculty expertise remains crucial in designing assessments, interpreting results, and providing nuanced feedback that considers the full context of student learning.

Academic Integrity in the AI Era. Rather than relying on detection tools, which research shows have significant accuracy problems and can unfairly impact non-native English speakers (Liang et al., 2023), institutions should focus on redesigning assessments and promoting responsible AI use. As demonstrated in previous research, AI-detection tools have high false positive rates and are particularly problematic for students from diverse linguistic backgrounds. Instead of trying to detect AI use, faculty should consider reimagining assignments to emphasize higher-order thinking and authentic assessment that leverage rather than prohibit AI tools. This might include having students explain their reasoning process, demonstrate their work through in-class activities, or use AI as a collaborative tool while explicitly documenting how they used it to enhance their learning. For example, rather than banning AI for writing assignments, instructors could require students to submit both their final work and a reflection on how they used AI tools to improve their writing process, encouraging transparency and developing critical thinking about AI's capabilities and limitations. This approach aligns with research showing that thoughtful AI integration can enhance rather than threaten academic integrity when properly structured (Mollick & Mollick, 2023).

C. Research Support

Research support refers to the integration of advanced technologies and tools that assist researchers in optimizing workflows, managing resources, and generating actionable insights to enhance productivity and collaboration. In the context of artificial intelligence (AI), these tools can enhance traditional research processes by automating complex tasks such as automated literature reviews, identifying research trends and gaps, and AI-assisted data analysis and visualization. By leveraging machine learning algorithms, natural language processing, and network analysis, AI-powered platforms empower researchers to enhance hypothesis generation, streamline bibliographic searches, uncover patterns across diverse datasets, and produce compelling visual insights that drive decision-making and innovation. These advancements promised not only enhance efficiency but also open new avenues for collaboration and discovery in academic and professional research domains.

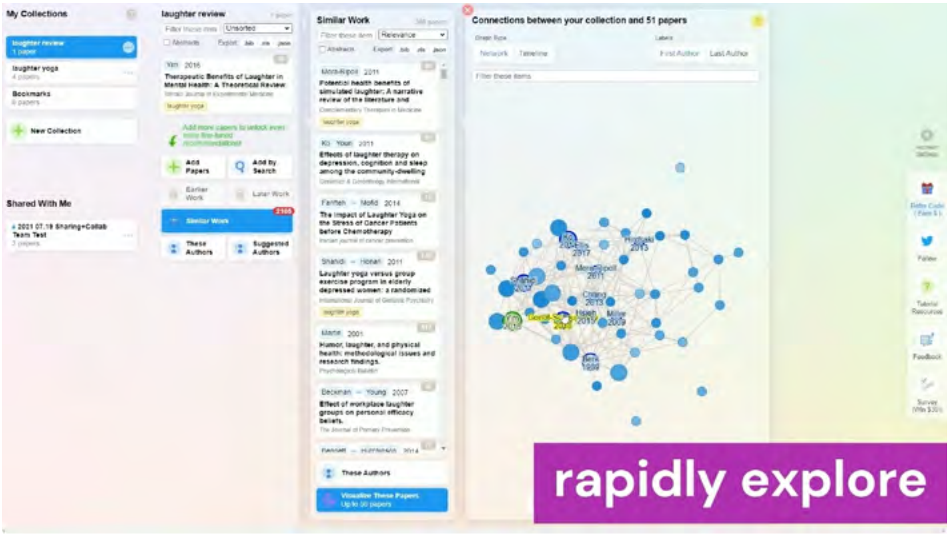
Google's AI co-scientist, a multi-agent system built on Gemini 2.0, has demonstrated its potential to enhance academic research productivity by generating novel hypotheses and accelerating the discovery process. This tool assists researchers by identifying emerging trends (biomedical discoveries, for instance), proposing innovative research directions, and streamlining complex analytical tasks (figure 6). Notably, the AI co-scientist consistently outperforms human experts and other AI models in hypothesis generation, with its Elo[5] rating surpassing 1700 over time. This indicates a significant improvement in the quality and originality of its contributions, allowing research teams to work more efficiently and focus on high-impact scientific advancements (Gottweis et al., 2025).

Automated Literature reviews and recommendations. Research Rabbit (figure 7) implemented at the Pontificia Universidad Católica de Chile (PUC), serves both faculties and researchers by simplifying the search and organization of scientific literature. This platform uses AI to deliver personalized article recommendations, synchronize with tools like Zotero (an open-source bibliographic reference manager developed by George Mason University), and provide interactive visualizations that uncover relationships between authors and research areas. By doing so, it saves researchers significant time in literature review, enabling them to build organized collections and focus on generating impactful insights. Furthermore, Research Rabbit facilitates institutional communication and integrates additional domains, such as social networks and reference search engines, creating a collaborative and enriched research ecosystem which allows to see connections between authors (figure 8) and shared articles collections. To support its adoption, PUC developed a comprehensive user guide through its [Centro de Desarrollo Docente UC](), offering internal consultations and support to ensure researchers can maximize the platform's potential effectively.

Figure 6. Practical Guide for Faculty at the Pontificia Universidad Católica de Chile.

5 Elo refers to a rating system used to evaluate the performance of AI-generated hypotheses. It is adapted from the Elo rating system in chess, where higher ratings indicate better performance. Here, it measures the quality and originality of hypotheses, comparing AI models against human experts.

Figure 7. Research Rabbit Interface.



Identifying research trends and gaps. At the University of Calgary, AI tools like Semantic Scholar, designed specifically for faculty members, research by identifying trends and gaps across a database of over 221 million scientific articles. By institutionalizing Semantic Scholar through its website, the university has fostered its widespread adoption, enabling the discovery of emerging research areas and collaboration. Among other free tools (appendix 1), Semantic Scholar leverages advanced technologies such as natural language processing, machine learning, and computer vision to streamlineacademic searches, automate literature reviews, and reveal critical research trends and gaps. While AI has limitations (Danler et al., 2024), it shows promising potential to mitigate biases like statistical (e.g., data imbalance), cultural (e.g., underrepresentation of minorities), and cognitive (e.g., confirmation bias) (Reyero Lobo et al., 2023).

AI-assisted analysis and visualization. Julius is utilized at both Harvard and Rice University to enhance the teaching of AI-driven analysis and data visualization. This platform integrates a comprehensive suite of AI technologies, including Large Language Models (LLMs), machine learning, predictive analytics, and advanced data processing frameworks. By combining these capabilities with a user-friendly interface, Julius empowers professionals and students to perform complex data analysis and extract actionable insights with ease. For researchers, it enables them to conduct advanced statistical analyses, such as ANOVA tests, correlation studies, and demographic analyses, in an accessible manner—even for those without extensive training in data science. While current evidence on Julius's impact on research outcomes remains limited, its integration into academic settings like Harvard and Rice University illustrates its potential. Future studies are expected to assess how these tools enhance research efficiency and quality, particularly for users with limited training in data science.

V STAFF-CENTERED INSTITUTIONAL TOOLS AND PRACTICES

AI-powered staff-centered tools are transforming management and institutional support by streamlining key processes within organizations. These tools provide advanced solutions such as campus management, AI chatbots for student queries, and resource allocation and scheduling, enabling more efficient and agile operations. Their implementation reduces operational burdens, enhances user experiences, and allows administrative teams to focus on higher-value strategic tasks. By integrating these technologies, institutions can significantly improve productivity and adapt quickly to the evolving needs of their communities.

D. Administrative and Institutional Support

In the field of administrative and institutional support, AI has demonstrated a significant impact, evident in the range of tools available for managing key processes such as academic administration, resource management, data-driven decision-making, and student support. The integration of these tools into various educational models and institutional systems, from the perspective of institutional strategic planning, can be traced to concepts such as Digital Transformation and Digital Education, among others. This approach not only reinforces institutional sustainability but also drives educational innovation, fostering new approaches to learning where AI has contributed valuable tools in a dynamic and competitive global environment.

De La Roca et al. (2024) discussed the impact of a chatbot on student learning and engagement. The findings suggest that students are more likely to perceive chatbots as valuable and beneficial in their educational context when they find them easy to use, highlighting features such as 24/7 assistance and user-friendly interface. This research discusses the importance of the perceived usefulness of AI chatbots among students, when effectively integrated into the teaching process. This virtuous approach can offer tangible benefits to teachers and staff like quick access to information, increased engagement and personalized learning experiences.

AI chatbots for students. A notable case is Penny, a chatbot implemented at Southern New Hampshire University (SNHU) in collaboration with EdSights. Penny serves both staff members and students and was developed to address the challenges of supporting a growing student population and improving retention rates. Tested through a randomized controlled trial (RCT), Penny utilizes conversational AI to proactively engage with students, addressing barriers such as academic perceptions, emotional well-being, and financial difficulties. While evidence on its long-term impact remains limited, this pilot study involved over 3,300 students and demonstrated a 1.4% increase in persistence rates and a 1.3% improvement in academic success within one term. Additionally, underrepresented groups saw even greater benefits, with a 2.5% increase in persistence for Black or African American students and 3.5% for Hispanic students. By automating routine tasks and identifying students in need of support, Penny allowed academic advisors to focus on more complex interventions, creating a more efficient and personalized approach to student success (EdSights, 2024).

AI chatbots for student, faculty and administrative queries. TECgpt is a promising generative AI-powered ecosystem designed by Tecnológico de Monterrey to personalize education, enhance learning processes, and streamline administrative and academic tasks. Built on Microsoft Azure's OpenAI Service[6] and incorporating advanced models like GPT-4 and DALL-E, this tool serves staff and faculty members along with students and is focused on four key areas: natural language processing with ChatGPT, image generation, ChatTEC tools, and custom generative AI models. Unlike standalone tools like ChatGPT, TECgpt is tailored to institutional needs, offering customized generative AI models and features like the Academic TECbot, which provides personalized assistance to students, faculty, and parents.

Students benefit from personalized support, such as TECbot, which addresses over 133 topics, automates 35 administrative processes, and offers personalized interactions, such as enrollment assistance, balance inquiries, and Canvas integration. Professors leverage tools like Skill Studio to craft dynamic teaching materials, automate routine tasks, and focus on creative pedagogy. By integrating privacy-first AI tools, TECgpt ensures secure interactions (Saavedra et al., 2024) while promoting academic growth and operational efficiency.

Campus Management, Resource Allocation and Scheduling. *Universidad Continental* in Peru has been implementing uPlanner tools since 2015 until present. Upplaner offers tools primarily for staff-members to address challenges in student retention, assessment, and operational efficiency. With a student population of over 63,000 across five campuses, the institution aimed to enhance its capacity to identify and support at-risk students early. Leveraging tools such as Curriculum Management and uAssessment, the university has optimized its evaluation processes. The recent inclusion of uBooking allows students to easily reserve various resources, while uForecast has streamlined enrollment prediction processes, enabling the institution to plan future periods with clarity.

Additionally, uRetention provides dropout risk projections, supporting the development of targeted retention strategies. This tool relies on traditional AI, i.e. supervised learning techniques, including AdaBoost and Random Forest, to generate actionable insights. Together, these tools enable timely interventions, such as counseling and resource allocation, while helping improve institutional planning and decision-making processes. This case highlights how uPlanner's AI-driven tools can enhance institutional management and sustain academic continuity in complex educational environments (uPlanner, 2015). As we noted earlier, evidence is limited, and more robust research is needed to accurately gauge the extent to which these tools are improving outcomes.

"AI-powered profiling and prediction can help identify at-risk students early on, enabling targeted support and guidance"

6 https://news.microsoft.com/source/latam/features/ai/tecnologico-de-monterrey-ai-ecosystem/?lang=en

E. Student Profiling and Prediction

In LAC, nearly half of enrolled students do not complete their degree by age 29, with about 50% dropping out during their first year (Ferreyra et al., 2017). Early dropout is often linked to institutional or curricular factors, such as the need to select a specific program from the first year, unlike more flexible systems in countries like the U.S. AI-driven profiling and prediction can help address this by identifying at-risk students early on, enabling targeted support and guidance to help them navigate critical decision points and adapt to academic demands, ultimately reducing dropout rates.

AI holds the promise to early identification of students at risk of poor performance, disengagement, or dropout. By analyzing data on behavior, performance, and participation, AI-driven tools can provide personalized interventions, helping students navigate academic challenges and make informed decisions. This targeted support aims to enhance retention, academic success, and administrative efficiency. Traditional AI methods, including supervised machine learning and rule-based systems, have effectively addressed these challenges for years. With the advent of generative AI, new opportunities arise to scale and improve these tools, further strengthening student support systems and reducing dropout rates.

Students Profiling and Prediction: Identifying at-risk students

Students Profiling and Prediction. Focus on identifying students who are at risk of underperforming or dropping out, enabling targeted interventions that enhance their likelihood of success. Examples include Mainstay's "Pounce" at Georgia State University, which primarily serves staff-members and students tackling challenges like "summer melt" –a phenomenon where admitted students fail to enroll due to barriers such as incomplete administrative processes, financial difficulties, or lack of guidance–by guiding students through enrollment tasks. Similarly, ConsiliumBots in Chile supports vulnerable students during the university application process by reducing errors and increasing their chances of admission. By providing timely and personalized support, these tools effectively address systemic barriers and improve educational outcomes.

Identifying at-risk students systems. A notable example is Mainstay, a traditional AI tool used at Georgia State University (GSU) under the name "Pounce." This intelligent virtual assistant was tested in a randomized controlled trial (RCT) to address "summer melt". Pounce achieved a 3.3% increase in enrollment rates and a 21% reduction in summer melt compared to the control group. Through proactive, personalized messages, Pounce supported students in completing key tasks such as Free Application for Federal Student Aid (FAFSA) forms and submitting academic transcripts, easing administrative burdens and demonstrating the scalability of this approach (Page & Gehlbach, 2017; Page et al., 2020).

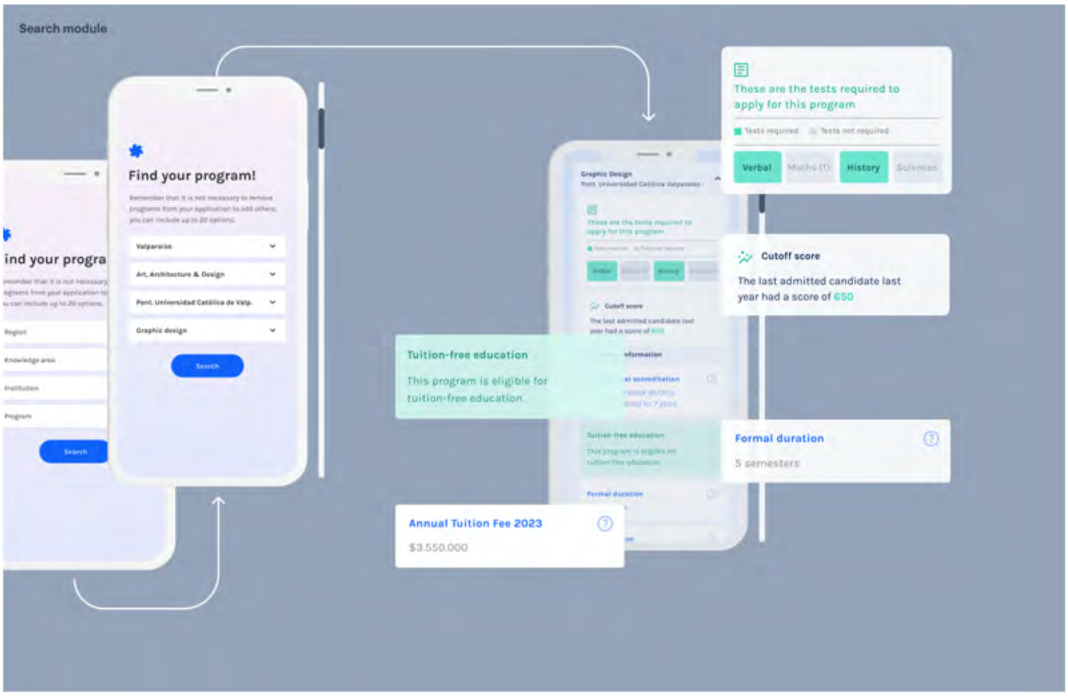
Chilean Case: Access to Higher Education

Students at Risk of Access and Enrollment. In Chile, a groundbreaking intervention has demonstrated the powerful impact of addressing information barriers in higher education access. Students from disadvantaged backgrounds often struggle with complex university application processes, lacking crucial information about their admission chances and program details. This information gap frequently results in application mistakes that can derail their higher education aspirations.

To tackle this challenge, Larroucau et al. (2024) implemented an AI-powered solution through ConsiliumBots. The system combines machine learning with deferred acceptance algorithms to provide personalized guidance to each applicant. The results were remarkable: students who previously would have remained unmatched to any institution saw their probability of successful assignment increase by 20%. Even more striking, undermatched students – those who typically enroll in less selective programs than their academic credentials would permit – improved their matches by 38%. Perhaps most significantly, the intervention tripled enrollment rates among beneficiary students.

These dramatic improvements in both match quality and enrollment rates demonstrate how technological solutions can effectively address systemic inequities in higher education access. The Chilean case provides compelling evidence that targeted information support, powered by AI, can transform the efficiency and fairness of university admissions systems.

Figure 8. Interface of ConsiliumBots Application: The application provides personalized support for higher education applicants by using AI-based tools to improve the selection process.



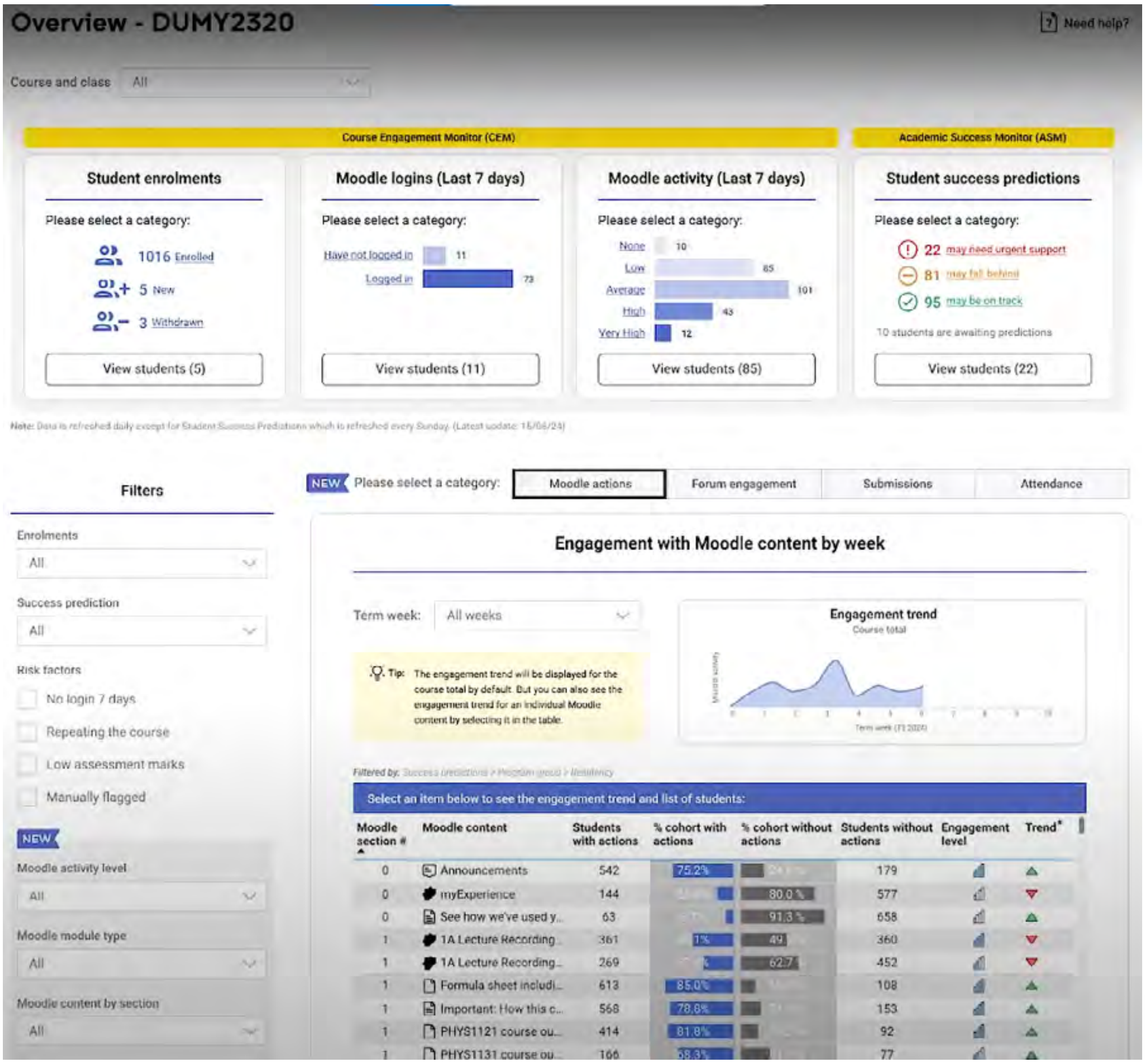
Predicting Academic Performance

Prediction systems go beyond profiling by using advanced analytics to forecast academic risks and recommend tailored support to students. The [Academic Success Monitor (ASM)] at UNSW exemplifies this capability, employing machine learning to detect early signs of underperformance and connect students with resources to improve engagement and outcomes. These predictive systems enable institutions to proactively address challenges, fostering more inclusive and supportive learning environments while enhancing overall academic performance.

Predicting underperformance in early academic journey. The University of South Wales (UNSW) in Australia has implemented the Academic Success Monitor (ASM), a machine learning-based system which serves both staff and faculty members, designed to identify and support students at risk of underperformance early in their academic journey. In a 2023 trial involving 33 academics and 25 courses, ASM accurately identified 79% of at-risk students[7] within the first few weeks. A larger pilot in 2024 expanded to 17,000 students across 80 courses, flagging 284 high-risk students and achieving significant results: 49% of students who received tailored recommendations improved their class participation, and 75% of academics reported earlier risk identification. Powered by Microsoft technologies like Azure Machine Learning Studio, ASM delivers personalized recommendations and facilitates proactive faculty engagement, reducing administrative workload while enhancing academic outcomes. This innovative, data-driven approach highlights UNSW's commitment to scalable, personalized, and ethical AI practices in HE, fostering more inclusive and supportive learning environments (Wagenaar, 2024).

7 Student at risk of academic failure can be defined as someone whose behavior and engagement patterns in the university's digital learning environment indicate potential challenges in achieving academic success. Some parameters are: Low engagement, missed deadlines, poor performance indicators (early assessment and quiz scores) and inconsistent participation.

Figure 10. ASM. Academic Success Monitor.



VI CHALLENGES

Implementing AI in higher education across Latin America involves a range of complex challenges. While some countries—such as Uruguay and Costa Rica—have made notable progress, others grapple with severe barriers that demand attention to ensure both equitable and effective AI integration. At the same time, global patterns reflect many of these same tensions: a recent study of 116 U.S. research institutions found that although 63% encourage AI use and half offer GenAI-based curricula, most still center on writing rather than broader applications, and fewer than half address key concerns like data privacy or intellectual property (McDonald et al., 2025). These findings highlight the urgent need for carefully crafted policies and guidelines that extend beyond localized, short-term fixes.

In Latin America, the additional disparities in digital readiness, infrastructure, and resources create an especially intricate landscape. Policymakers, institutional leaders, and educators must coordinate closely to ensure AI delivers on its promise of improved educational outcomes rather than simply adding new layers of complexity. The following sections examine these challenges in greater detail—from infrastructure gaps and teacher preparedness to regulatory hurdles and algorithmic bias—underscoring the multifaceted nature of AI implementation in the region.

A. Infrastructure and Access Barriers

The most fundamental challenge facing AI implementation in Latin American higher education is the persistent digital divide. While countries like Uruguay and Costa Rica have made significant progress in developing their digital infrastructure, many regions still face serious challenges with basic connectivity and access to technology. The lack of reliable internet connectivity, particularly in rural areas, creates a significant barrier to AI adoption in educational settings. This issue is particularly acute in remote regions where basic infrastructure like consistent electricity access remains a challenge.

> **"The region's limited production of AI patents, accounting for only 0.21% of global AI patents, reflects a broader struggle to develop and scale AI solutions"**

The absence of advanced networking technologies, such as 5G networks, further limits the potential for implementing sophisticated AI tools that require high-speed, low-latency connections. This technological gap is particularly problematic for applications like real-time AI tutoring or adaptive learning systems that require constant, stable internet connections.

Emerging technologies like Starlink present promising solutions for expanding connectivity to underserved areas. These satellite-based systems offer the potential to provide high-speed internet access to remote regions that have traditionally been difficult to serve with conventional infrastructure. However, significant barriers to adoption remain, including the high cost of compatible devices and the need for technical expertise to maintain and support these systems. Additionally, the total cost of ownership, including maintenance and ongoing support, creates substantial financial burdens for many institutions (Shaengchart & Kraiwanit, 2023; Hallet & Valdivia Lefort, 2023).

B. Teacher Preparedness and Professional Development

A critical challenge in AI adoption is preparing educators to effectively integrate these technologies into their teaching practices. The current landscape reveals significant gaps in AI literacy among faculty and staff across Latin American higher education institutions (ILIA, 2024, pag. 85). This challenge is compounded by the uneven development of AI training programs across different institutions and regions, leading to disparities in technological readiness and implementation capabilities.

Professional development programs face several key challenges. First, there is often a significant gap between the technical skills needed to effectively implement AI solutions and the current capabilities of faculty and staff. Second, the rapid pace of AI development means that training programs must constantly evolve to remain relevant. Finally, there are substantial disparities in access to training resources between well-resourced institutions and those with limited funding, threatening to widen existing educational inequities.

C. Regulatory and Ethical Frameworks

The regulatory landscape for AI in education varies significantly across Latin America, creating challenges for consistent implementation and cross-border collaboration. While some countries, such as Chile and Uruguay, have established comprehensive AI strategies and data protection laws, others remain in the early stages of regulatory development. This disparity creates uncertainty and potential risks in AI implementation, particularly in light of varying data privacy regulations, inconsistent requirements for algorithmic transparency, and unevenly applied ethical guidelines for AI use in education.

Progress in Data Protection and sector-specific AI strategies. Most countries in the region have introduced legislation on personal data protection and are at various stages of crafting national or sector-specific AI strategies. As illustrated in Table 7 (appendix 3), several nations are moving ahead with policies adapted to their contexts:

- **Peru** focuses on infrastructure development and ecosystem-building to facilitate AI adoption.
- **Chile** emphasizes human well-being, safety, and respect for individual freedoms in its AI initiatives.
- **Uruguay** integrates ethics, human rights, and participatory governance into AI policymaking.
- **Colombia** views AI as an accelerator for a comprehensive digital transformation in both public and private spheres.
- **Ecuador** remains in the diagnostic and analytical phases, working toward a regulatory framework conducive to AI growth.
- **Brazil** adopts a holistic approach, organizing AI strategy around nine thematic pillars, including legislation, ethics, public safety, and sectoral tools.

Despite these varying degrees of progress, the lack of harmonized frameworks across the region poses three critical challenges. First, fragmented data privacy regulations impede region-wide solutions and the sharing of best practices. Second, divergent requirements for algorithmic transparency create operational hurdles for institutions active in multiple jurisdictions, potentially limiting AI's beneficial applications. Third, ethical guidelines for AI in education differ substantially in their depth and enforcement, raising concerns around student privacy, fairness, and educational equity. Addressing these inconsistencies through more unified policies and shared standards will be crucial for maximizing AI's positive impact across Latin America.

D. Algorithmic Transparency

Algorithmic transparency refers to the ability to understand, explain, and justify how AI systems function, particularly in automated decision-making processes. This concept is especially crucial in sectors such as education, healthcare, and public administration, where algorithms can significantly influence outcomes. One of the most formidable obstacles is the so-called "algorithmic black box," which arises from technical complexity, hidden intentions, or inherent design limitations that obscure how decisions are made. Transparency thus needs to be addressed at two key stages: ex ante, when users are informed about a system's design and limitations, and ex post, when clear explanations of decisions are provided to facilitate audits and reviews (Coglianese & Lehr, 2019; Memarian & Doleck, 2023).

Within Latin America, the regulatory landscape surrounding algorithmic transparency varies considerably. As noted in Table 7 (see appendix 3) and further elaborated in Table 9 (see appendix 5), Chile leads the region with its General Instruction on Algorithmic Transparency, establishing a foundational framework for the use of algorithms in public administration. Uruguay has similarly made strides by focusing on guidelines and recommendations related to data traceability, transparency, and explainability. Still, the review reveals a lack of specific guidance for ESUP, highlighting both the challenges and opportunities for advancing algorithmic transparency in the educational sector across the region.

E. Algorithmic Bias and Fairness

The challenge of algorithmic bias presents particular concerns in educational contexts, where AI systems can inadvertently perpetuate or amplify existing inequalities. Recent research has shown that AI systems used in education often reflect and reinforce societal biases, particularly when making predictions about student performance or automating assessment processes. A meta-analysis by Thiem et al. (2020) revealed that one in three social research studies were affected by algorithmic bias, with one in ten studies being severely compromised.

These biases manifest in multiple ways within educational settings. Predictive models for student performance often show varying accuracy rates across different demographic groups, potentially disadvantaging students from underrepresented backgrounds (Yu et al., 2021; Baker & Hawn, 2021). Assessment systems, particularly those using automated grading, have demonstrated systematic biases in how they evaluate work from students of different nationalities or linguistic backgrounds. Geographic location also plays a role, as models often perform better in contexts similar to where they were trained, potentially disadvantaging students in LAC institutions when using systems developed elsewhere. Table 4 reviews a list of biases associated with the use of AI-based systems.

Table 4: Review of Biases Associated with the Use of Artificial Intelligence-Based Systems.

Category of Bias	Description	Examples
Prediction of Student Outcomes	Algorithms used to predict academic performance reveal inequalities among different student groups.	Retention and graduation prediction models show varying rates of false positives and negatives based on race and gender (Chouldechova, 2017).
Performance Assessment	Automated essay grading systems assign scores that differ from those given by human evaluators.	Automated grading systems tend to underestimate or overestimate students from certain nationalities (Li et al., 2021).
Geographic Location	Models perform better in countries where they were trained but show less accuracy in other countries.	Student emotion detectors work more effectively in specific populations than in mixed ones (Ocumpaugh et al., 2014).
Socioeconomic Background	Models predict worse outcomes for students from low-income or disadvantaged backgrounds.	Models tend to predict low performance for low-income students (Yu et al., 2020; Yu et al., 2021).
Additional Factors	Biases are observed in students with disabilities, non-native languages, military connections, or regional dialects.	Models are less accurate for students with disabilities, military connections, or non-native speakers (Guo et al., 2019; Baker et al., 2020).
Data Collection and Preparation	The way data is collected and prepared can introduce systematic biases into the model.	Non-representative datasets create evaluation biases, and the improper use of models adds further biases (Barocas et al., 2019).
Problem Definition	The selection of the target variable and features can reflect prior biases and skew results.	Defining 'success' solely by GPA may overlook other achievements, while features like access to advanced classes can bias outcomes (Kleinberg et al., 2017).

The Netherlands case study of the Education Executive Agency (DUO) provides a stark example of how algorithmic bias can impact educational systems. Their risk profiling system disproportionately flagged students with non-European migration backgrounds as high-risk, leading to discriminatory practices in student finance eligibility assessments. This case demonstrates the critical importance of implementing robust bias detection and mitigation strategies in educational AI systems (Algorithm Audit, 2024).

Bias Detection Tool is a tool designed to identify user groups that may be unfairly treated by AI systems, using unsupervised learning statistical methods such as clustering. This tool is part of the OECD Catalogue Tools & Metrics for Trustworthy AI[8], that enables the detection of indirect or intersectional discrimination without requiring sensitive data such as gender, nationality, or ethnicity. It also allows users to select a performance metric to define bias. The tool uses the Hierarchical Bias-Aware Clustering (HBAC) algorithm to process both numerical and categorical data while preserving privacy by running entirely on the user's device without transmitting information to third parties. The results include PDF or JSON reports that highlight the clusters with the highest bias, describing their characteristics so that human experts can assess potential cases of discrimination or inequity. This approach combines privacy, detailed analysis, and results visualization, providing a solid foundation for addressing biases in AI-based systems.

F. Privacy and Security Concerns

As AI adoption increases in higher education, data protection and security have become increasingly critical concerns. Latin American institutions must navigate complex requirements for protecting student data while leveraging the benefits of AI-powered educational tools. This challenge is particularly acute given the sensitive nature of educational data, which often includes personal information, academic records, and behavioral data.

Several countries in the region have made significant progress in establishing data protection frameworks. Chile's Law 21.719 focuses on creating a Data Protection Agency, while Uruguay has maintained a comprehensive regulatory framework since 2008 that governs the storage, processing, and use of personal data in AI applications. These frameworks must balance the need for data protection with the potential benefits of AI-powered educational innovation.

The implementation of effective data governance requires several key measures. Impact assessments have become essential tools for identifying and mitigating risks before deploying AI solutions. Algorithm registries help ensure traceability and transparency in algorithmic systems. The appointment of data protection officers has emerged as a critical step in safeguarding data and ensuring compliance with regulations. However, many institutions struggle to implement these measures effectively due to resource constraints and technical complexity.

G. Ecosystem Development

LAC faces significant challenges in building a robust AI innovation ecosystem for education. The region's limited production of AI patents, accounting for only 0.21% of global AI patents as of 2022, reflects a broader struggle to develop and scale AI solutions (Stanford University, 2024). This limitation stems from multiple factors, including insufficient funding for research and development, limited coordination between academic institutions and industry partners, and a shortage of startups focused on educational AI solutions.

The region shows particular weakness in developing advanced AI competencies. While basic machine learning skills are growing, there is limited expertise in cutting-edge areas such as Large Language Models and AI model training (ILIA, 2024, pag. 110). This gap is exacerbated by brain drain, as skilled AI professionals often leave the region for opportunities in more developed markets. The situation creates a circular problem where the lack of local expertise makes it harder to develop and implement effective AI solutions, which in turn limits the growth of local AI capabilities.

8 https://oecd.ai/en/catalogue/overview

The development of student-centered AI tools faces particular challenges in the region. While countries like Brazil, Chile, and Uruguay have made progress in building infrastructure and regulatory frameworks, there remains a significant gap in creating and scaling solutions that address the specific needs of Latin American educational institutions. The Latin American Artificial Intelligence Index (ILIA) highlights how this lack of investment restricts the ability to scale promising projects and limits innovation in the educational technology sector.

Furthermore, the ecosystem suffers from a fragmented approach to innovation and development. The disconnect between academic research, industry needs, and educational requirements often results in solutions that fail to address the specific challenges faced by Latin American institutions. This situation is exacerbated by limited funding opportunities for educational technology startups and insufficient mechanisms for sharing best practices and successful implementations across the region.

H. Implementation and Integration Challenges

The practical implementation of AI in educational settings presents significant operational challenges. Institutions must navigate the complex process of integrating AI tools into existing curricula, administrative systems, and teaching practices. This integration requires careful consideration of institutional readiness, faculty capabilities, and student needs.

Many institutions struggle with the technical aspects of AI implementation, including system compatibility, data integration, and maintenance requirements. The cost of implementation extends beyond the initial investment in technology to include ongoing expenses for training, support, and system updates. Additionally, institutions must develop new protocols and procedures for managing AI-enhanced educational processes while ensuring academic integrity and maintaining educational quality.

The successful integration of AI also requires significant cultural change within educational institutions. Faculty and staff must adapt to new ways of teaching and working, while students need support in developing the digital literacy skills necessary to benefit from AI-enhanced education. This cultural transformation represents a significant challenge that requires sustained effort and careful change management strategies.

I. Resource Allocation and Sustainability

The allocation of resources for AI implementation in higher education represents a significant challenge across Latin America. While the potential benefits of AI are clear, institutions face difficult decisions in balancing investments in AI technology against other pressing needs. The challenge is particularly acute for public institutions that operate under strict budgetary constraints and must justify technological investments against traditional educational expenditures.

Sustainability presents another critical dimension of the resource challenge. Beyond initial implementation costs, institutions must plan for ongoing maintenance, updates, and support of AI systems. This includes not only technical maintenance but also continuous professional development for faculty and staff, regular content updates, and periodic system evaluations. Many institutions struggle to develop sustainable funding models that can support these long-term requirements while ensuring equitable access to AI-enhanced education.

The disparity in resources between institutions threatens to exacerbate existing educational inequities. Well-funded institutions can invest in sophisticated AI solutions and provide comprehensive support for their implementation, while institutions with limited resources may struggle to provide even basic AI-enhanced learning opportunities. This resource gap risks creating a two-tiered educational system where access to AI-enhanced education becomes a privilege rather than a standard educational tool.

VII CONCLUSION: HARNESSING AI FOR AN INCLUSIVE AND TRANSFORMATIVE HIGHER EDUCATION SYSTEM

Artificial intelligence (AI) is rapidly redefining the landscape of higher education, offering unprecedented opportunities to enhance access, learning outcomes, and institutional efficiency. From AI-powered adaptive learning platforms to intelligent administrative tools, these innovations hold the potential to address long-standing inefficiencies and structural inequities. Recent empirical evidence demonstrates AI's concrete impact: students using well-designed AI tutors learn more than twice as much in less time compared to traditional methods, while AI-powered admissions systems have increased placement efficiency by 20% and improved outcomes for underserved students by 38%. These results underscore AI's ability to optimize admissions, personalize learning experiences, and streamline institutional processes, thereby fostering a more resilient and inclusive education system.

However, realizing AI's full potential in Latin America requires an approach tailored to the region's unique challenges and opportunities. Current adoption levels remain uneven, hindered by infrastructure deficits, low AI patent contributions (only 0.21% globally), and a shortage of local AI-driven educational innovations. Faculty surveys reveal significant gaps: while 61% have used AI in teaching, 80% report lacking institutional guidelines for implementation. To bridge these gaps, a concerted effort is needed to increase investments in AI research, strengthen local innovation ecosystems, and develop robust public-private financing mechanisms. Initiatives such as educational technology incubators and regional AI consortia could catalyze the development of scalable, contextually relevant AI solutions.

Beyond investment, capacity building is paramount. The effective integration of AI depends on upskilling educators, administrators, and policymakers. Research shows that thoughtful implementation is critical - while basic AI integration can show initial performance improvements, carefully designed systems that promote active learning and prevent overreliance achieve significantly better outcomes. Programs like Uruguay's computational thinking workshops for teachers serve as models for equipping faculty with the technical competencies needed to leverage AI-driven tools (González, 2021). Yet, these efforts must be accompanied by strategies to retain talent, addressing the ongoing brain drain that limits the region's ability to sustain and scale AI innovations.

> **"The time to act is now. Through strategic investments, inclusive policies, and ethical AI governance, Latin America has the opportunity to harness AI as a catalyst for educational transformation"**

Equally critical is the imperative to bridge the digital divide. AI's potential will remain unrealized if vast segments of the population, particularly in rural and underserved areas, lack access to essential digital infrastructure. Evidence from successful implementations shows that combining AI tools with comprehensive support systems can triple enrollment rates and significantly improve student outcomes, but these benefits depend on reliable access. Expanding broadband connectivity, ensuring affordable access to AI-powered tools, and embedding AI literacy in curricula are foundational steps toward equity-driven AI adoption.

The ethical governance of AI in higher education cannot be overlooked. Issues such as algorithmic bias, data privacy, and the opacity of AI-driven decision-making demand urgent attention. Research reveals concerning patterns of bias affecting non-native speakers and students from underrepresented backgrounds, highlighting the need for robust safeguards. Regulatory frameworks like Chile's General Instruction on Algorithmic Transparency provide useful precedents for ensuring fairness and accountability in AI deployment, but more comprehensive approaches are needed across the region.

Achieving these objectives requires a multisectoral approach. Governments, universities, the private sector, and civil society must collaborate to develop policies that balance innovation with ethical safeguards. Successful initiatives demonstrate how strategic partnerships can drive meaningful change – from AI-powered student support systems reducing dropout rates to centralized admission platforms improving equity in access. By fostering regional and international cooperation, Latin America can not only adopt AI but shape its development to reflect the region's educational priorities and social imperatives.

"Evidence from successful implementations shows that combining AI tools with comprehensive support systems can triple enrollment rates"

The AI revolution in higher education is not an abstract future—it is an unfolding reality demanding immediate attention and thoughtful action. The time to act is now. Through strategic investments, inclusive policies, and ethical AI governance, Latin America has the opportunity to harness AI as a catalyst for educational transformation. The evidence presented in this report demonstrates that when implemented thoughtfully, AI tools can significantly enhance educational outcomes while promoting equity and access. Success will require sustained commitment from all stakeholders, careful attention to implementation details, and unwavering focus on ethical considerations and student needs. By taking decisive action today, the LAC region can ensure that all students—regardless of background—benefit from the transformative potential of AI in education.

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IX APPENDIX

Appendix 1.

Name	Pricing	Category
scite.at	Monthly fee	Search, Summarize, Analyze
Assistant by scite	Free (Beta)	Search, Summarize, Analyze
Iris.ai	Monthly fee	Visualize, Summarize, Manage, Analyze
Research rabbit	Free	Visualize, Summarize, Manage
Scispace	Free	Search, Summarize
ChatGPT	Free and monthly fee	Write, Summarize, Analyze
Consensus	Free	Search, Summarize
Elicit	Free and monthly fee	Search, Summarize
ChatPDF	Free	Summarize
Google Bard	Free (Beta)	Write, Summarize
Jenni AI	Free and monthly fee	Write, Summarize
Semantic scholar	Free	Search, Summarize
OpenRead	Free and monthly fee	Search, Summarize
Trinka	Free and monthly fee	Write
Microsoft Copilot	Free	Write, Summarize
Scholar GPT	Free	Search, Summarize

Table 5. Tools for Research Based on the Article "Quality and Effectiveness of AI Tools for Students and Researchers for Scientific Literature Review and Analysis" (Danler et al., 2023). Own elaboration.

Appendix 2.

Ranking	Argentina	Brasil	Chile	Costa Rica
1	Sentiment Analysis	Speech Recognition	Pattern Recognition	Artificial Intelligence (AI)
2	Artificial Intelligence (AI)	Sentiment Analysis	Unsupervised Learning	Pattern Recognition
3	Pattern Recognition	Artificial Intelligence (AI)	Statistical Inference	Predictive Modeling
4	Decision Trees	Unsupervised Learning	Artificial Intelligence (AI)	Neural Networks
5	Convolutional Neural Networks (CNN)	Decision Trees	Decision Trees	Deep Learning
6	Unsupervised Learning	Pattern Recognition	Neural Networks	Neural Networks
7	Algorithm Analysis	Machine Learning Algorithms	Supervised Learning	Supervised Learning
8	Artificial Neural Networks	Classification	Convolutional Neural Networks (CNN)	Convolutional Neural Networks (CNN)
9	Supervised Learning	Statistical Inference	Predictive Modeling	Predictive Modeling
10	Neural Networks	Supervised Learning	Natural Language Processing (NLP)	Natural Language Processing (NLP)

Table 6: AI engineering skills with the highest year-on-year (YoY) growth, by country (2023). Prepared by the authors based on ILIA, 2024.

Appendix 3.

Country	Sectoral Policies and National Strategies	Relevant Laws and Regulatory Frameworks
Chile	National Policy on Artificial Intelligence implemented in 2021, seeks to promote the development and ethical use of AI in various sectors. Focus on TP education and university articulation.	Bill 15869-19: Under discussion since April 2023, it regulates AI systems, robotics and related technologies. Law 21.719 on the protection of personal data of 2024 harmonizes the standard with the European Union.
Perú	National Artificial Intelligence Strategy: In development to boost AI adoption in the country.	Personal Data Protection Act: Regulates data processing, relevant to AI tools. Law 31.814 which promotes the use of artificial intelligence for economic development.
Bolivia	No specific national strategy: Currently, Bolivia does not have a national AI strategy.	Law 1.080 on Digital Citizenship: Article 12 provides for the protection of personal data. There is no personal data protection law.
Ecuador	Situation diagnosis on AI: An initial diagnosis has been carried out to assess the status of AI in the country.	Personal Data Protection Act: Approved in 2021. Draft Organic Law on Regulation and Promotion of AI.
Uruguay	National Artificial Intelligence Strategy 2024-2030.	Law 18.331 on personal data protection, in force since 2008, it serves to regulate the processing of personal data in AI contexts.
Colombia	National Policy for Digital Transformation and Artificial Intelligence Established in 2019, it lays ethical and strategic foundations for AI.	Bill 059/23 seeks to regulate public policy guidelines for the development, use and implementation of AI.
Brasil	Brazilian Artificial Intelligence Strategy:Launched in 2021, it guides the development and use of AI in the country.	General Data Protection Act (LGPD): In force since 2020, it regulates the processing of personal data, which is essential for AI tools. Bill 2338/23: Proposes a specific regulatory framework for AI, based on a risk approach.

Table 7: Review of the legal and regulatory framework for AI in Latin America.

Appendix 4.

Country	Number of incoming investments	Total estimated value of incoming investment
Argentina (ARG)	16,35	27,42
Bolivia (BOL)	4,69	0,36
Brasil (BRA)	35,39	46,56
Chile (CHL)	100	100
Colombia (COL)	26,57	38,97
Costa Rica (CRI)	0,68	0
Cuba (CUB)	35,08	60,13
Ecuador (ECU)	4,5	0,32
El Salvador (SLV)	4,69	0,46
Guatemala (GTM)	0	0,8
Honduras (HND)	4,69	0,36
Jamaica (JAM)	5,34	0
México (MEX)	26,36	20,29
Panama (PAN)	3,21	0,65
Paraguay (PRY)	0,74	0
Perú (PER)	8,6	0,76
Rep. Dominicana (DOM)	4,6	0
Uruguay (URY)	40,18	92,74
Venezuela (VEN)	0,68	0,1
LAC	16,97	20,52

Table 8. Number of incoming investments; and Estimated value of incoming investment in AI.

Appendix 5.

Country	Level of Advancement in Algorithmic Transparency	Considerations on Algorithmic Transparency
Perú	**Initial Level:** At this stage, there is a recognition of the importance of transparency in the use of AI.	It seeks to adopt ethical guidelines for the sustainable, transparent, and replicable use of AI. Emphasis is placed on clear definitions of responsibilities regarding the proper use of data and the protection of individuals' privacy and identity. It promotes information transparency while safeguarding citizens' privacy (See appendix 4).
Uruguay	**Intermediate Level.** Principles and guidelines for transparency in the use of AI have been established[9], but implementation is still in progress.	Transparency and explainability are crucial for the ethical and responsible use of AI. It is essential to ensure the traceability of the datasets used by AI systems. These systems must be transparent so that the public can understand how they are managed. The aim is to provide assurances for the ethical and responsible use of AI systems.
Chile	**Regional Leader:** It has developed a General Instruction (GI) on Algorithmic Transparency for public administration[10],, becoming the first country in the region to establish such a guideline.	Transparency and explainability are essential for inclusive AI, with an emphasis on data quality.Establishing standards and recommendations for algorithmic transparency in critical public sector tools. Ensuring the identification of biases in algorithms and databases, as well as mitigating risks to fundamental rights. Providing information on how algorithms function and the data they use.
Colombia	**From Initial to Intermediate Level:** While public policies and ethical frameworks have been adopted, their implementation and the enforcement of transparency remain limited.	The importance of state transparency and citizen participation is emphasized. The need for trusted and high-quality digital services is acknowledged. Public algorithm repositories have been created, though their use and updates are still limited. Efforts are being made to ensure accountability in relation to automated decisions.
Ecuador	**Initial Level:** It is beginning to address algorithmic transparency, focusing on the need for clear regulatory frameworks.	Emphasis is placed on transparency in the training and development of AI tools, accompanied by clear ethical principles. AI systems must be grounded in transparency and effective communication with citizens. There is a need to develop clear and specific regulations for algorithmic transparency.
Brasil	**Intermediate Level:** It promotes transparency and explainability in AI systems[11], focusing on ethical and responsible use.	It encourages a commitment to transparency and responsible disclosure. The importance of explainability in decisions made by automated systems is emphasized. Automated decisions must be explainable and interpretable. The use of open data in AI development is encouraged. There is a recognized need to adhere to ethical principles in the development and use of AI, including transparency and accountability.

Table 9: Review of the Development of Algorithmic Transparency in Latin America.

9 https://www.gub.uy/agencia-gobierno-electronico-sociedad-informacion-conocimiento/comunicacion/publicaciones/recomendaciones-sobre-transparencia-algoritmica
9 https://www.consejotransparencia.cl/wp-content/uploads/instruccion/2024/09/Informe-recomendaciones-congreso-CPLT.pdf
11 https://www.transparencia.org.br/downloads/publicacoes/Recomendacoes_Governanca_Uso_IA_PoderPublico.pdf

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