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AI implementation in higher education in Latin America and the Caribbean

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Preface

AI is rapidly reshaping our world and higher education with it. It is transforming how faculty teach, students learn and are assessed, and how institutions operate. Higher education is the education sector with the highest rate of digital technology adoption, and the rapid development of AI in recent years has made it imperative to examine how systems can both regulate and harness new technologies to promote equity, quality and efficiency.

Against this background, *AI implementation in higher education in Latin America and the Caribbean*, produced by the UNESCO International Institute for Higher Education in Latin America and the Caribbean (UNESCO IESALC) in cooperation with the United Nations University Institute for the Advanced Study of Sustainability (UNU-IAS), offers a valuable evidence base and presents regional experiences that earlier works have under-represented. In covering 200 higher education institutions across 19 countries in Latin America and the Caribbean (LAC), the study maps the use of AI in teaching and learning, research, community engagement and administration, and examines whether and how it is governed.

The findings present a clear picture. AI is already widely used across higher education but governance has not kept pace. While 87 per cent of institutions in LAC report using AI in at least one area of their activities, only 26 per cent have a formal AI strategy. Adoption is largely bottom-up, driven by individual faculty and students and sustained by internal champions rather than national or institutional policy. This pattern is consistent with how higher education has met previous waves of technology, but the distinctive scale and speed of AI amplify both the potential promises and risks.

Systematic gaps between public and private higher education institutions can also be observed, with private institutions leading in several areas, particularly formal strategy and staff training. The equity implications of these gaps reach well beyond higher education itself and also highlight the importance of sustainable financing models and capacity development.

While these findings emerge from a specific regional context, the tensions they reveal are global in nature. Today, in an era shaped by AI and related breakthrough innovations, UNESCO remains committed to ensuring that technology serves equity, opportunity and sustainable development, underpinned by ethical principles and a human-centred approach. UNESCO's seminal work in this area began in 2019 with the adoption of the *Beijing Consensus on Artificial Intelligence in Education*. This momentum continued with the landmark *Recommendation on the Ethics of Artificial Intelligence*, adopted in 2021. Building on these foundations, UNESCO has developed a series of publications and frameworks, including AI competency frameworks for both teachers and learners.

The study does more than document the present; it provides a series of actionable recommendations and challenges us to reflect on a more fundamental question about the evolving mission of higher education and its future in a world deeply integrated with AI. Maximizing benefits rests on sustained investments in access and capacity and strengthened digital literacy and governance frameworks that ensure ethical use, transparency and accountability while keeping educational purposes at the forefront.

I am confident that the findings and recommendations will prove valuable to higher education institutions, policy-makers and organizations working to navigate the complexities of AI integration. As a pioneering regional study, it offers important insights not only for LAC but also for the broader global conversation on the future of higher education in the age of AI.



Borhene Chakroun
Interim Director - UNESCO IESALC

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AI implementation in higher education in Latin America and the Caribbean was prepared by the UNESCO International Institute for Higher Education in Latin America and the Caribbean (UNESCO IESALC), in collaboration with the United Nations University Institute for the Advanced Study of Sustainability (UNU-IAS).

The study was developed under the guidance of Borhene Chakroun, Director of the Division for Policies and Lifelong Learning Systems and Interim Director of UNESCO IESALC. Arianna Valentini from UNESCO IESALC served as the lead author, with important contributions from Jonghwi Park and Jerome Silla on the study design and questionnaire development.

Our sincere gratitude extends to the staff from 200 higher education institutions across 19 countries in Latin America and the Caribbean who participated in the questionnaire that underpins this study. Their valuable experiences and insights were essential to shaping this work.

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Acronyms and abbreviations

- **AI** – Artificial intelligence
- **C4AI** – Center for Artificial Intelligence
- **GDP** – Gross Domestic Product
- **GDPR** – General Data Protection Regulation
- **GPT** – Generative Pre-trained Transformer
- **ILIA** – Latin American Artificial Intelligence Index
- **IMF** – International Monetary Fund
- **ISCED** – International Standard Classification of Education
- **IT** – Information technology
- **LAC** – Latin America and the Caribbean
- **OECD** – Organisation for Economic Co-operation and Development
- **RAI UK** – Responsible AI, United Kingdom
- **TEQSA** – Tertiary Education Quality and Standards Agency, Australia
- **UC** – University of California system
- **UCLA** – University of California, Los Angeles
- **UKRI** – UK Research and Innovation
- **UNEP** – United Nations Environment Programme
- **UNESCO** – United Nations Educational, Scientific and Cultural Organization
- **UNESCO IESALC** – UNESCO International Institute for Higher Education in Latin America and the Caribbean
- **UNITWIN** – University Twinning and Networking programme (UNESCO)
- **UNU-IAS** – United Nations University Institute for the Advanced Study of Sustainability
- **SINAES** – Sistema Nacional de Acreditación de la Educación Superior (National Accreditation System for Higher Education, Costa Rica)
- **SINEACE** – Sistema Nacional de Evaluación, Acreditación y Certificación de la Calidad Educativa (National System to Assess, Accredit, and Certify Educational Quality, Peru)
- **SNAATCA** – Sistema Nacional de Asignación, Acumulación y Transferencia de Créditos Académicos (National System to Allocate, Accumulate, and Transfer Academic Credits, Mexico)
- **SNCA** – Sistema Nacional de Créditos Académicos (National Academic Credit System, Colombia)
- **SNCA-PY** – Sistema Nacional de Créditos Académicos (National Academic Credit System, Paraguay)
- **SNCL** – Sistema Nacional de Competencias Laborales (National System of Workplace Competencies, Mexico)
- **SUCA** – Sistema Universitario Centroamericano (Central American University System)
- **SUNEDU** – Superintendencia Nacional de Educación Universitaria (National Superintendency for University Education, Peru)
- **TQF-J** – Tertiary Qualifications Framework (Jamaica)
- **UCJ** – University Council of Jamaica (Jamaica)
- **UCR** – Universidad de Costa Rica (University of Costa Rica, Costa Rica)
- **UCU** – Universidad Católica del Uruguay (Catholic University of Uruguay, Uruguay)
- **UNA** – Universidad Nacional (National University, Costa Rica)
- **UNED** – Universidad Estatal a Distancia (State Distance-Learning University, Costa Rica)
- **UNESCO IESALC** – UNESCO International Institute for Higher Education in Latin America and the Caribbean
- **UNESCO UIS** – UNESCO Institute for Statistics

AI implementation in higher education in Latin America and the Caribbean

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Executive summary

Artificial intelligence (AI) is transforming higher education at an unprecedented pace offering significant opportunities for teaching, learning and administration while at the same time introducing ethical and governance challenges. The speed of AI adoption is outpacing institutional readiness, with many higher education institutions integrating AI before establishing the policies, capacities and oversight needed to manage its risks effectively.

AI implementation in higher education in Latin America and the Caribbean provides a comprehensive regional evidence base on how higher education institutions in the region are integrating AI across five key dimensions – teaching and learning, research, community engagement, administration and institutional governance. The study draws on a sample of 200 higher education institutions across 19 countries in Latin America and the Caribbean (LAC). It provides both a baseline to measure progress and a roadmap for the journey ahead through a series of targeted recommendations for higher education institutions, policy-makers and intergovernmental organizations.

The findings reveal widespread but uneven adoption of AI. The majority of higher education institutions (87 per cent) report using AI in at least one area, with higher rates observed among private higher education institutions. Teaching and learning (74 per cent) show the highest rate of AI adoption, with the majority of institutions relying on general purpose AI tools such as ChatGPT, Copilot and Gemini. AI use is also significant in research (57 per cent) to accelerate data analysis and improve quality, while adoption is lower in administration (34 per cent) and community engagement (20 per cent). Across several areas, institutional leaders are unaware of AI use within their own institutions, suggesting that adoption is often driven by faculty, researchers and students rather than institutional strategy or guidance.

The governance of AI in higher education is a key challenge. Only 1 in 4 higher education institutions reports having a formal AI strategy, with few reporting dedicated oversight and formal monitoring and evaluation mechanisms. AI training also remains uneven, with stronger support for academic staff but fewer opportunities for administrative staff and students, contributing to growing concerns about the ethical use of AI and academic integrity.

Institutional leaders identify staff training and internal champions of AI as the two main enablers of its adoption, while insufficient funding, limited expertise, gaps in training and concerns around data privacy and bias remain the principal barriers. Overall, the findings highlight the need to align widespread AI adoption with stronger governance, more inclusive capacity development and coordinated policy action at institutional, national and global levels.

Accordingly, the study identifies a set of recommendations for key stakeholders:

- Higher education institutions should aim to develop comprehensive AI strategies that embed governance from the outset; establish a dedicated AI governance structure with student representation; make AI literacy a graduation-level competency; extend AI training to administrative and technical staff; incorporate robust monitoring and evaluation frameworks into AI implementation; and strengthen academic integrity through assessment redesign.
- National policy-makers should aim to integrate higher education into national AI strategies; establish dedicated public funding mechanisms for AI implementation and governance; develop national guidance on AI and academic integrity; integrate AI literacy and governance into quality assurance and accreditation frameworks; and invest in regional data infrastructure and a shared evidence base on AI outcomes in higher education.

- Regional and international organizations should aim to support the development of a shared regional evidence base on AI in higher education; provide targeted technical assistance to strengthen AI governance capacity in higher education institutions; and mobilize development finance to build AI governance capacity across higher education systems.

Introduction

The world is witnessing the unprecedented surge of artificial intelligence (AI) in higher education, creating both urgent challenges and opportunities for transformation. UNESCO's 2026 *Higher Education Global Trends Report* reveals that digitalization features prominently in the higher education plans of most countries, with 77 per cent including dimensions related to digital education services, AI, and online and remote learning. As of 2024, 56 countries had adopted national AI strategies, the majority of which underline the critical role of higher education in AI education, research and innovation. More than half these countries had already launched AI graduate programmes to encourage highly skilled professionals in the field (UNESCO IESALC, 2026).

Yet institutional readiness has not kept pace with AI adoption, a pattern that is historically consistent with how higher education has responded to previous technology waves, but which carries heightened consequences given AI's distinctive scale and risk profile (Isaifan, 2026; Jin et al., 2025; Palvia et al., 2018). A 2025 survey of 400 UNESCO Chairs and UNITWIN Network members across 90 countries found that while 9 in 10 respondents reported using AI tools in their professional work, only 19 per cent of their institutions had adopted a formal AI policy, while a further 42 per cent were in the process of developing guiding frameworks (UNESCO, 2025).

Understanding what is at stake first requires being clear about the missions of higher education. The 2026 *UNESCO Transforming Higher Education* roadmap affirms that higher education performs three interconnected purposes that serve the public interest: (i) teaching and learning, (ii) knowledge production and dissemination and (iii) social responsibility through community engagement, and that universities increasingly leverage the interconnection between these purposes to their advantage (UNESCO, 2026). This framing matters because it establishes that AI's significance in higher education cannot be reduced to any single dimension, whether labour market preparation, research productivity or administrative efficiency. AI is reshaping all three missions simultaneously, and its governance must be understood accordingly. It also provides the normative foundation for this report's analytical framework which maps AI adoption across teaching and learning, research, community engagement, administration and its institutional governance.

The changing demands of the labour market are frequently cited as the central driver of this transformation, but this represents one dimension in a broader and contested set of pressures. Structural shifts in how knowledge is produced and validated, the emergence of synthetic science, changes in academic labour, and the growing role of non-academic actors in research and innovation, are equally significant. Within this wider context, the International Monetary Fund (IMF) estimates that nearly 40 per cent of global employment is exposed to AI, rising to around 60 per in advanced economies. Of those exposed jobs in advanced economies, roughly half may face negative effects while the rest could benefit from productivity gains, depending on the degree of complementarity between AI and human labour as well as on policy responses (Cazzaniga et al., 2024).

For LAC these global projections do not translate directly. Uneven digital infrastructure and variable AI readiness shape the conditions of adoption in ways that the predominantly high-income country literature does not adequately capture. The region must prepare graduates for AI-integrated labour markets while navigating structural constraints that most global AI frameworks overlook. The region has seen remarkable growth in student enrolment in higher education (ISCED levels 5–8) since the turn of the century. Enrolment rates nearly tripled from 12 million in 2000 to more than 31 million in 2024, yet persistent completion and equity gaps remain (UNESCO IESALC, 2026). Marginalized

groups, including low-income students, Indigenous peoples and people with disabilities continue to face significant barriers to higher education access and success that enrolment growth alone has not resolved (UNESCO IESALC, 2024). At the same time, the pace of AI adoption in higher education institutions across the region is accelerating, often outpacing the institutional governance structures, human capacities and regulatory frameworks needed to support it in a responsible way (Jin et al., 2025; Pireci Sejdiu and Sejdiu, 2025; UNESCO IESALC, 2025a).

Faculty-level data reinforces the significance of this moment for the region specifically. Among the four world regions surveyed by the Digital Education Global AI Faculty Survey in 2025, Latin American faculty stand out as the most optimistic: 78 per cent view AI as an opportunity – the highest of any region – compared to 70 per cent in Asia and the Pacific; 65 per cent in Europe, Middle East and Africa; and 57 per cent in the United States and Canada. Latin American faculty also report the highest intention to incorporate AI in their future teaching – at 96 per cent – against a global average of 86 per cent (Digital Education Council, 2025).

Against this backdrop, this report maps AI adoption and implementation across universities in LAC across five dimensions: (i) teaching and learning, (ii) research, (iii) community engagement, (iv) administration and (v) governance. Drawing on a regional survey conducted among 200 higher education institutions in 19 countries of LAC between August and October 2025, it offers an institution-level picture of where AI is being used, how it is being governed, what capacities exist and what challenges remain The findings are meant to inform institutional leaders and national policy-makers working to integrate AI responsibly, ethically and inclusively, and to support regional and international cooperation in advancing a shared agenda on AI in higher education.

This report is organized into seven sections beginning with the methodology and characteristics of survey respondents presented in Section 1. Section 2 introduces critical perspectives on AI integration while Section 3 maps patterns of AI adoption across the five above mentioned dimensions. Continuous professional development for university actors is examined in Section 4 and Section 5 assesses governance and institutional readiness covering AI strategies, budget allocation, policies and academic integrity, governance structures and monitoring and evaluation mechanisms. Section 6 investigates challenges to AI integration and the report ends with conclusions and recommendations and a proposed set of priority knowledge areas for higher education leaders in Section 7. The seven sections are complemented by annexes focusing on priority areas for AI leadership and a survey administered among universities in the region.

1. Methodology

This report maps AI adoption across five domains: (i) teaching and learning, (ii) research, (iii) community engagement, (iv) the administrative function and (v) institutional readiness and governance. These domains encompass the conditions required to enable, guide and sustain AI integration in an ethical and responsible way including strategy, finance, regulation, academic integrity, structure, capacity and culture, and evaluation.

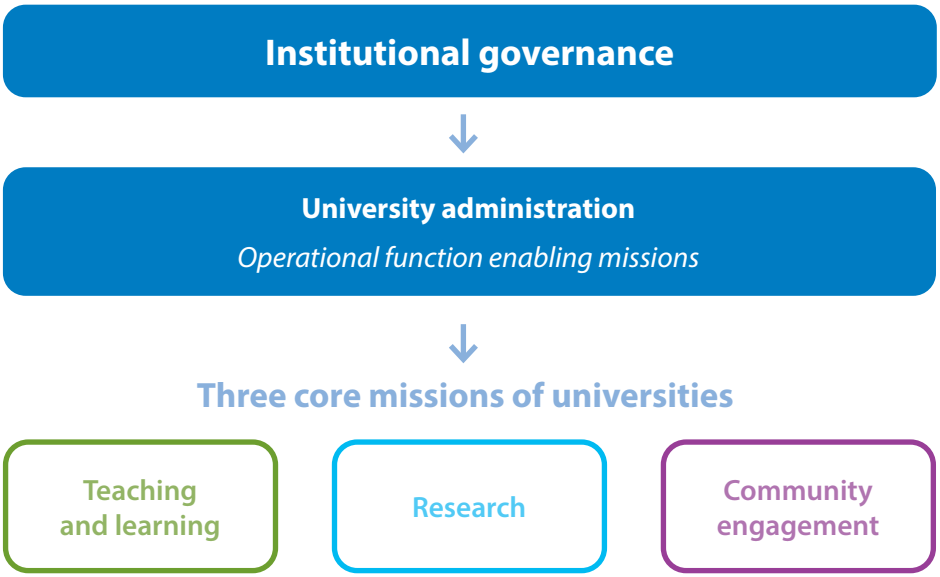
1.1 Theoretical framework

The contemporary university is a multi-mission institution the purpose of which cannot be reduced to a single activity. The theoretical framework underpinning the report address this complexity by analysing each of the five distinct dimensions (Figure 1).

Over the past century higher education theory has converged on the three-mission model. Teaching (or education) and research are conventionally identified as the first and second missions of universities while a growing body of literature from the 1980s onward formalized a third mission, the university's contribution to society beyond the academic community, encompassing technology transfer, community service, public engagement and knowledge-based regional development (Jongbloed et al., 2008; Compagnucci and Spigarelli, 2020). The 2026 *UNESCO Transforming Higher Education Roadmap* reaffirms this architecture and recognizes that not only do the three missions interlace and overlap but that universities increasingly leverage this interconnection to their advantage (UNESCO, 2026).

These three missions do not exist in isolation. They are situated within a broader and thriving debate about the role of the university in the age of generative AI, one that extends well beyond questions of tool adoption or digital transformation. At stake are structural questions about how knowledge is produced, validated and disseminated when AI systems can generate, synthesize and simulate scholarly output at scale, a phenomenon sometimes referred to as synthetic science. Part of the debate centres on questions around academic labour: who produces knowledge, under what conditions and with what institutional recognition, at a moment when the boundaries between human and machine-generated intellectual work are increasingly blurred. In addition, the fact that much of AI's infrastructure lies in the hands of a small number of private technology firms is at odds

Figure 1. Dimensions of the theoretical framework



with the university's public mission. Moreover, the dominance of English-language, Global North content in the training data of leading AI systems prompts urgent questions about epistemic diversity about whose knowledge counts, in what language and from which institutional context.

These are not peripheral concerns. They shape the conditions under which AI is adopted, governed and experienced across higher education systems globally, and with consequences for LAC. The five-dimension framework used in this report (teaching and learning, research, community engagement, administration, governance) is designed to map institutional-level adoption and readiness. The findings it generates should be interpreted as part of an ongoing conversation about what universities are for and what they risk becoming in an AI-integrated world.

The three missions describe what universities exist to accomplish but not the organizational machinery used. Administration fills that role. It is not a fourth mission but rather the operational infrastructure enabling the three missions and encompassing financial management, human resources, student services, facilities, information technology, legal compliance, admissions, enrolment management and the coordination of academic processes. The significance of AI in administration is different from that involved in teaching or research. AI-driven administrative applications in this domain, from student support chatbots and early warning systems to admissions algorithms and financial planning tools, operate primarily on institutional data and shape the conditions under which students and staff experience the university (Khairullah et al., 2025; Molina and Medina, 2025). For this reason, administration is included as a distinct analytical dimension as it serves to determine how the three missions are pursued and with what results.

Neither the three missions nor the administration dimension address whether AI adoption is ethical, responsible, effective, equitable or sustainable. This is the role of governance, which is frequently confused with administration. Administration refers to the operational execution of institutional functions. Governance refers to the structures, rules, norms and decision-making processes through which authority is exercised, accountability is maintained and institutional direction is set (Bleiklie and Kogan, 2007). It is the architecture within which administration operates and through which missions are implemented.

The distinction is important in the context of AI adoption. Administrative decisions, such as whether to deploy a student early warning system, may be made and executed by management. However, whether such a system is accountable, equitable and aligned with the institution's values is a governance question and concerns who decides, on what basis, through what deliberative process and with what mechanisms for oversight, correction and accountability. UNESCO's *Transforming Higher Education Roadmap* is explicit that the policy and governance challenge around AI is 'to ensure that AI and digital technologies promote the sustainable development agenda and are employed to remedy rather than exacerbate existing inequalities and global asymmetries in higher education access and quality' (UNESCO, 2026).

The inclusion of governance as a structured, multi-component analytical dimension is grounded in two complementary theoretical frameworks. The Technology-Organization-Environment framework establishes that the adoption of technology in organizations is shaped not only by the characteristics of the technology itself, but by organizational factors (including resources, managerial structures and internal capacities) and environmental conditions, including regulatory frameworks and external support (Baker, 2012).

This provided the rationale for examining governance not as a single variable but as a set of distinct conditions that together constitute the institutional context in which AI adoption takes place. Rogers' Diffusion of Innovations theory complements this by distinguishing between the initial adoption of an innovation and its subsequent institutionalization, a distinction that informed the decision to assess not only whether institutions have adopted AI, but whether the organizational

conditions necessary for sustained and accountable integration are in place (García Aviles, 2020; Jin et al., 2025; Khairullah et al., 2025). The governance and readiness subcomponents examined in this report (formal AI strategies, dedicated budgets, policy frameworks, governance structures, academic integrity mechanisms, equity considerations and monitoring systems) operationalize the organizational and environmental conditions that both frameworks identify as consequential for how technology diffuses and becomes embedded within institutions.

1.2 Data collection and validation processes

This report is based on data collected through an online survey (see Annex II for the full questionnaire) designed to map the adoption and implementation of AI in higher education in LAC across the five dimensions presented in section above (2.1). The survey was administered between August and October 2025 in Spanish and English to ensure widespread coverage across the region.

The survey was developed by the UNESCO IESALC UNU-IAS and consists of 33 questions organized around the five above mentioned dimensions. It was directed at a specific type of respondent within each institution, namely, senior institutional and academic leaders at rector, dean and strategic planning levels.

The survey was disseminated through two main channels. It was shared via social media platforms (UNESCO IESALC Newsletter and LinkedIn) and distributed directly through UNESCO IESALC networks and higher education associations in the region, including networks in the Caribbean subregion. Despite these outreach efforts, Caribbean representation in the final dataset remains limited. Cuba is the only Caribbean country with valid responses (n=7), and while responses were received from Jamaica, these were excluded during data cleaning due to incompleteness. The findings of this report should therefore be read as reflecting primarily the Latin American higher education systems in the region, rather than the full breadth of LAC. The survey was also circulated through social media opening up the possibility that individuals outside the target profile, such as educators or students, may have submitted responses.

A total of 375 responses were received and underwent a data cleaning process to ensure the validity and relevance of the dataset. Responses were excluded if they came from individuals outside the target respondent profile, if they were incomplete, if they originated from countries outside the Latin America and Caribbean region, or if more than one response was received from the same institution, in which case only the response from the most appropriate respondent was retained. Following this process, n=200 valid responses were included in the final analysis, representing universities across 19 countries.

1.3 Survey respondents

The analysis draws on n=200 valid responses representing universities across 19 countries in the region. Given the self-selected nature of the sample and its geographic concentration, findings should be interpreted as indicative of trends and patterns rather than statistically representative of the region as a whole.

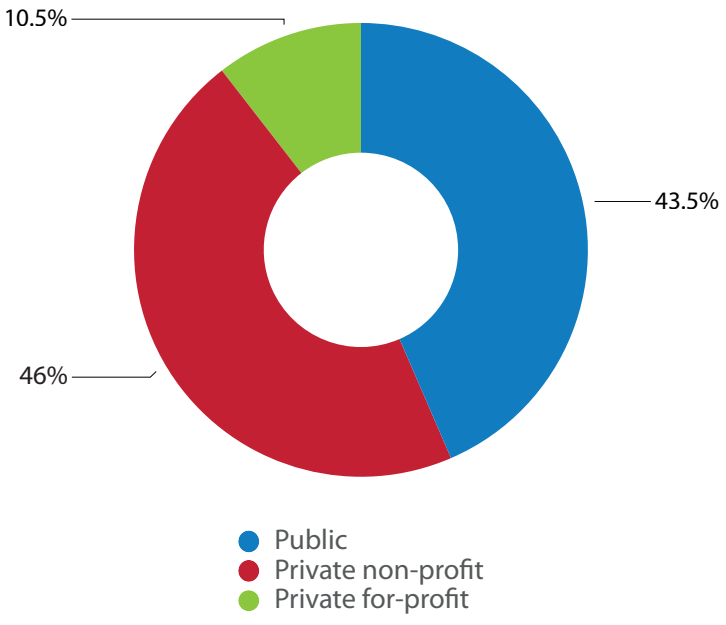
Colombia was the most represented country with 40 institutions, followed by Mexico (30) and Argentina (27). Together these three countries, which have among the largest higher education systems in the region, account for nearly half of the total sample. Smaller contributions came from other countries, with the full distribution by country presented in **Table 1**.

In terms of institution type, the sample is divided between public and private universities (for-profit and non-profit). This is particularly important for the LAC which has the highest rate of private enrolment in the world, with nearly 1 in every 2 students attending a private higher education institution (UNESCO IESALC, 2026). In this study, public institutions account for 43.5 per cent of the sample, private non-profit institutions for 46 per cent and private for-profit institutions for the remaining 10.5 per cent (**Figure 2**).

Table 1. Proportion of participating institutions by country

Country	n
Colombia	40
Mexico	30
Argentina	27
Peru	15
Bolivia	15
Chile	8
Costa Rica	8
El Salvador	8
Paraguay	8
Cuba	7
Venezuela (Bolivarian Republic of)	7
Ecuador	6
Brazil	5
Honduras	5
Panama	4
Guatemala	3
Puerto Rico, United States	2
Dominican Republic	1
Uruguay	1
TOTAL	**200**

Figure 2. Distribution of participation by institution type



Considering the academic orientation of the sample, most universities (77 per cent) identify as multidisciplinary and only 15 per cent and 8 per cent consider themselves specialized and technological, respectively (**Figure 3**).

The distribution of the sample varies considerably by institution type, reflecting structural differences in how public and private higher education is organized in the region. Public universities tend to be large institutions: 42 per cent of those that participated in this study enrol more than 15,000 students, making them the institution type most likely to operate at scale. By contrast, private for-profit universities are considerably smaller: 52 per cent enrol fewer than 5,000 students, and a further 33 per cent fall in the medium range of 5,000 to 15,000 students, meaning that fewer than 15 per cent are large institutions.

Private non-profit universities occupy an intermediate position, with the majority being small- to medium-sized: 42 per cent have under 5,000 students and 46 per cent fall in the medium category, with only 12 per cent enrolling more than 15,000 students (**Table 2**).

Size differences are even more pronounced when examined by academic orientation. Specialized universities are almost entirely small institutions: 70 per cent enrol fewer than 5,000 students and only 7 per cent are large. Polytechnic universities are also predominantly small (56 per cent under 5,000 students), with only 13 per cent enrolling more than 15,000 students. Multidisciplinary universities show the most balanced size distribution, with 27 per cent small, 43 per cent medium and 30 per cent large, the only academic profile group where large institutions represent a meaningful share (**Table 3**).

Figure 3. Distribution of participating institutions by academic orientation

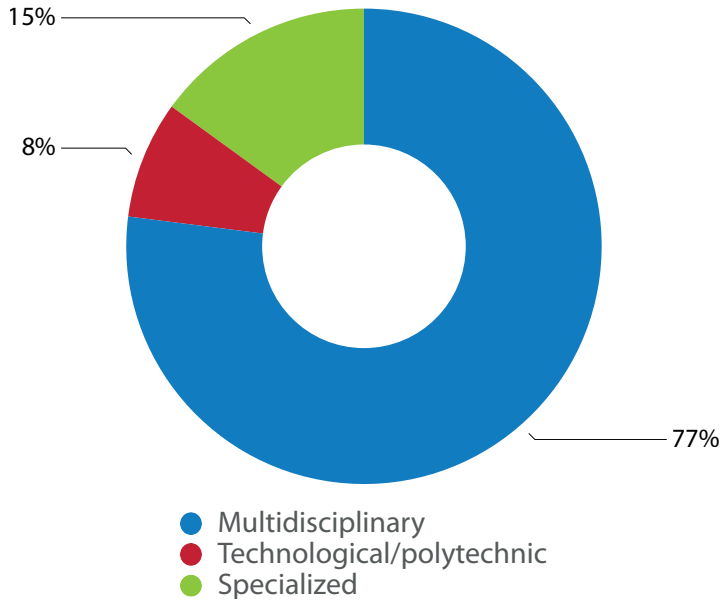


Table 2. Size of participating institutions by institution type (Percentage)

Institution size	Public (n=87)	Private non-profit (n=92)	Private for-profit (n=21)
Under 5,000 students	25	42	52
5,000–15,000 students	33	46	33
Over 15,000 students	42	12	15

Table 3. Size of participating institutions by academic orientation (Percentage)

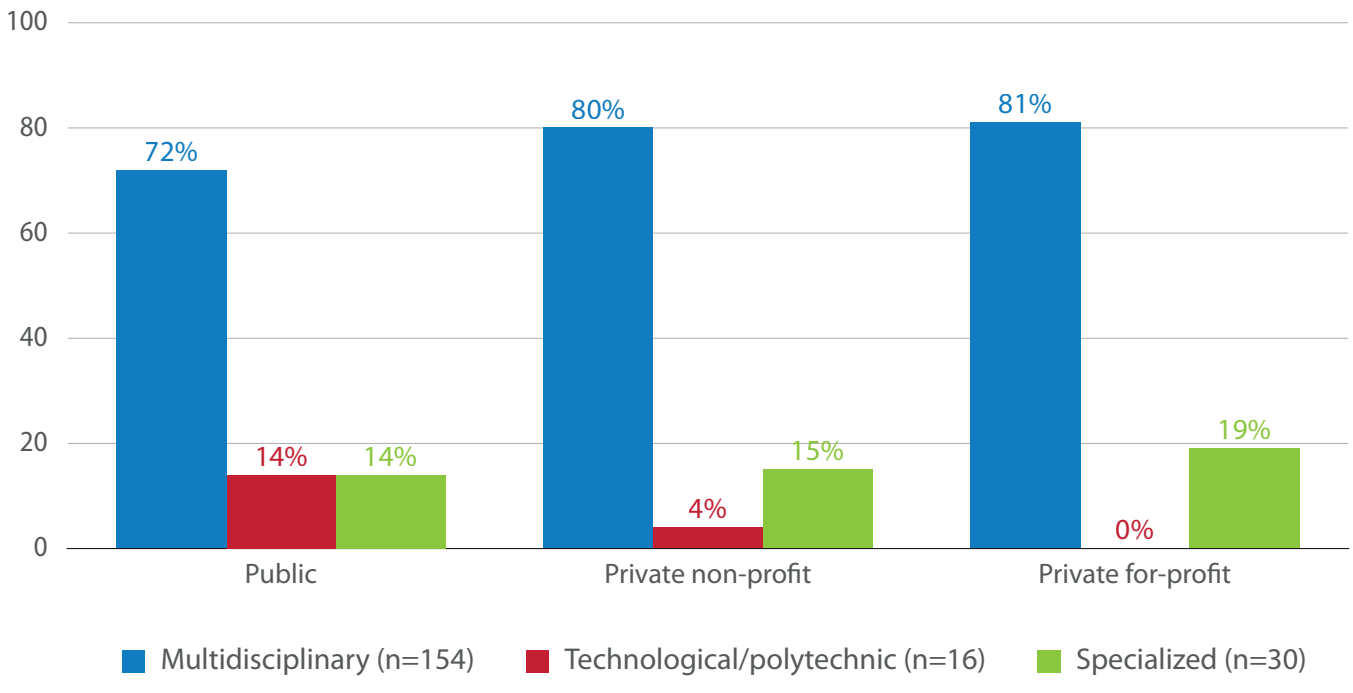
Institution size	Multidisciplinary (n=154)	Technological/polytechnic (n=16)	Specialized (n=30)
Under 5,000 students	27	56	70
5,000–15,000 students	43	31	23
Over 15,000 students	30	13	7

Reading across both classification variables simultaneously reveals several structural features of the sample that are important when interpreting the findings throughout the report.

As shown in **Figure 4**, most universities in the sample are multidisciplinary regardless of institution type (72 percent of public universities, 80 percent of private non-profit universities and 81 per cent of private for-profit universities). This means that multidisciplinary universities effectively drive the overall sample figures and differences between academic profile groups should be read with this in mind.

The most significant finding throughout the report concerns polytechnic universities: 75 per cent of all polytechnic universities in the sample are public institutions, with the remaining 25 per cent being private non-profit. There are no for-profit technological or polytechnic universities in the sample. This compositional feature is important when interpreting this group's results throughout the report. Several of the patterns observed for polytechnic universities – including lower management commitment, higher reliance on national policy as an enabling factor and lower rates of dedicated AI budgets – may partly reflect their predominantly public character rather than their academic orientation. The two variables are not fully separable for this group and claims about the distinctive behaviour of polytechnic universities should be read with this in mind. Moreover, the breakdown per academic orientation leaves

Figure 4. Distribution of academic profile within each institutional type



polytechnic universities at n=16 which, while sufficient to identify broad patterns, limits the robustness of group-level comparisons. Findings related to this group should therefore be interpreted with caution and are presented as indicative rather than conclusive throughout the report.

1.4 Data analysis

Considering the mapping purpose of the report, the data analysis in the following sections is descriptive. The aim is to provide a picture of the current state of AI adoption and implementation across the region. Throughout the report, data is analysed against two main variables: the universities' institutional type (public, private non-profit and private for-profit) and academic orientation (multidisciplinary, technological or polytechnic and specialized).

While the public-private classification was a question in the same survey, the academic orientation was a classification undertaken *ex post*. It was conducted manually by the research team through a systematic review of each institution's official webpage, examining the range of undergraduate programmes offered. This raw classification produced 17 distinct categories, a level of granularity that is too fragmented to allow for reliable descriptive analysis as several categories contained only one or two responses, meaning that any percentages derived from them would be based on an insufficient number of cases to be meaningful.

Based on this review, institutions were therefore consolidated into three broader groups: multidisciplinary, polytechnic and specialized. Institutions offering a broad range of programmes across multiple disciplines (including those operating primarily in distance or hybrid modalities) were classified as 'multidisciplinary' (n=154). Institutions with a clear technological or polytechnic orientation were retained as a distinct category, 'polytechnic' (n=16), given their relevance to questions of AI adoption. All remaining institutions with a narrower or domain-specific academic focus were consolidated under 'specialized' (n=30), covering fields such as health sciences, business and economics, arts and humanities, teacher training and others.

1.5 Limitations

Several limitations of this study should be kept in mind when interpreting the findings presented throughout this report.

Sampling and representation. The dataset is based on a self-selected convenience sample distributed through UNESCO IESALC and UNU networks, higher education associations and social media platforms. While efforts were made to reach institutions across the region, participation was voluntary and responses were not collected through a randomized or stratified sampling process. The sample is geographically concentrated, with nearly half of all responses coming from three countries (Colombia, Mexico and Argentina), which also represent among the five largest higher education systems in the country. Findings should therefore be interpreted as indicative of trends and patterns rather than as statistically representative of the region. Where the report refers to patterns across the region, this should be understood as patterns observed within this sample rather than as generalizable claims about all higher education institutions in LAC.

Caribbean under-representation. Despite outreach efforts to networks in the Caribbean subregion, Caribbean institutions are significantly under-represented in the final dataset. Cuba is the only Caribbean country with valid responses (n=7), and while responses were received from Jamaica, these were excluded during the data cleaning process. As a result, the report's findings speak much more to the Latin American higher education context than to the Caribbean and conclusions should not be generalized to the Caribbean subregion without further dedicated research.

Evidence base and available literature. This report contributes to a field in which the empirical evidence base remains nascent and rapidly evolving. The critical perspectives mapped in Section 2 draw on a growing but still limited body of peer-reviewed research, alongside industry reports and grey

literature, which vary considerably in methodological rigour and independence. Where industry-produced or non-peer-reviewed sources are cited, this reflects the current state of available evidence rather than an equivalence of credibility with academic research. Readers are encouraged to weigh sources accordingly. The field of AI in education is generating new empirical evidence at pace, and some findings cited in this report may be revised or nuanced as that evidence base matures.

Respondent profile and self-reporting bias. The survey was directed at senior institutional and academic leaders at rector, dean and strategic planning levels. While this design choice reflects the report's focus on institutional-level adoption and governance, it means that findings reflect leadership perceptions rather than the direct experiences of faculty, students or administrative staff. Self-reporting by institutional leaders may also introduce optimism bias, as respondents may be inclined to present their institutions' AI readiness and governance in a favourable light. These factors should be considered when interpreting findings related to policy implementation, training provision, and monitoring and evaluation.

2. Critical perspectives on AI integration in higher education

As AI becomes increasingly embedded in higher education systems worldwide, a growing body of concern has emerged within academic communities about the risks of insufficiently governed integration. The following subsection maps the most consistently documented concerns in the recent literature, followed by additional challenges that are gaining attention and are particularly relevant to the LAC context.

2.1 Cognitive implications

A growing strand of research, although nascent, warns that frequent, unreflective reliance on AI tools may erode the cognitive capacities that universities seek to develop, specifically, the ability to reason independently and think critically. While AI tools can support personalized learning, excessive reliance on them may reduce cognitive engagement and long-term memory retention (Bai et al., 2023). Gerlich (2025) identified a negative correlation between frequent AI use and critical thinking abilities, and a study of 580 university students found that AI dependency was negatively associated with critical thinking, with cognitive fatigue operating as a mediating factor (Tian and Zhang, 2025). Empirical studies have documented concerns about the impact on critical thinking and transversal competencies, particularly in technical and professional programmes (Baidoo-Anu and Ansah, 2023; Sanchez Ruiz et al., 2023). The pedagogical implication is clear: AI tools introduced without deliberate instructional redesign risk embedding dependency rather than developing competence – a risk that is heightened wherever adoption outpaces pedagogical guidance. At the same time, the study of AI's implications for cognitive development is nascent and any conclusions should be approached with caution.

The phenomenon described above is increasingly referred to as 'cognitive offloading', the delegation of cognitive tasks to external tools in ways that may reduce internal cognitive engagement and the development of durable skills (Risko and Gilbert, 2016). In the LAC context, emerging evidence suggests this dynamic is already visible. A documented case from Colombia illustrates the immediacy of this challenge: following Meta's embedding of AI bots into WhatsApp, Facebook and Instagram in July 2024, students across the country, including in rural areas previously less exposed to these tools, rapidly began using them to complete homework without meaningfully engaging with learning tasks (Salamanca, 2025).

2.2 Academic and research integrity

Generative AI has fundamentally complicated the terrain of academic honesty. In 2024, the International Center for Academic Integrity reported that 58 per cent of students admitted using AI tools dishonestly to complete assignments (Tan and Maravilla, 2024). The challenge is deepened by genuine ethical ambiguity: students frequently do not equate AI-assisted work with traditional plagiarism, while faculty often cannot detect it or reach consistent judgments about acceptable use (Kofinas et al., 2024; Lund et al., 2025). For the research mission, the stakes are equally serious. Large language models are known to produce hallucinations, posing a direct threat to scientific rigour where researchers lack the training or incentive to verify AI-generated content before use (Kofinas et al., 2024; Rudolph et al., 2023).

2.3 Algorithmic bias

AI systems reflect the data on which they were trained and that data carries structural inequalities (Marwala, 2026). Among higher education administrators, concerns about bias in AI models rose from 36 per cent to 49 per cent in a single year (Ellucian, 2024). In the LAC context, these risks are compounded as most AI tools are trained predominantly on English language, Western-centric content, creating gaps in their capacity to serve the region's linguistic and cultural diversity (Guo et al., 2024; Kofinas et al., 2024). Empirical evidence from Peru further illustrates this vulnerability. A

study across 21 universities found that a significant proportion of both students and faculty perceived an absence of clear institutional policies on data privacy and AI governance and that ethical challenges such as algorithmic bias remain poorly understood and inadequately addressed at the institutional level (Marín et al., 2025). That so little empirical research exists on how algorithmic bias specifically manifests in LAC educational contexts can signal that institutions in the region may be scaling discriminatory practices through AI tools without the evidence base needed to detect or challenge them.

2.4 Data privacy and surveillance

AI systems in education require access to large amounts of student data (academic performance, behavioural patterns, interaction histories and in some cases biometric data). This creates significant data protection risks, particularly when tools are deployed through third-party commercial platforms with unclear data governance practices (Klimova and Pikhart, 2025). A study of AI usage guidelines at world-ranked universities found that privacy and security are a central concern across institutional policies and that regulatory gaps, especially around the use of student metadata by AI vendors, remain inadequately addressed in many national contexts (Ng et al., 2025). The fear of surveillance, or of loss of control over personal information, has also been associated with increased student and staff anxiety (Klimova and Pikhart, 2025). For institutions in LAC, many of which lack national data protection frameworks of the breadth of the General Data Protection Regulation (GDPR) in the European Union, the exposure is considerable and a significant proportion of students and faculty members report perceiving an absence of clear institutional policies on privacy in AI use (Marín et al., 2025).

2.5 Environmental costs

The environmental footprint of AI is substantial and growing. Data centres currently consume an estimated 415 terawatt-hours of electricity globally (approximately 1.5 per cent of global power demand) and the International Energy Agency projects that figure could more than double by 2030 (IEA, 2024; Mitul and Vijaykumar, 2025). Training Generative Pre-trained Transformer 4 (GPT-4), one of the most widely used models in higher education today, is estimated to have consumed around 50,000 megawatt-hours of electricity, approximately 40 times more than its predecessor GPT-3 (Ludvigsen, 2023). The consequences can already be seen at the industry level. Google reported that its total carbon emissions rose 51 per cent from its 2019 baseline, reaching 11.5 million tonnes, attributing the increase directly to AI-driven data centre and supply chain expansion (Google, 2025). Microsoft's overall emissions have increased by 23.4 per cent compared to its 2020 baseline, despite commitments to carbon neutrality, with 97 per cent of its footprint driven by the energy and materials required for data centre construction to support AI and cloud services (Microsoft, 2025). Water consumption has followed a similar trajectory: Google's data centres increased their water use by 17 per cent in a single year, with the company acknowledging that AI expansion is the primary driver (Google, 2025). These costs sit uneasily alongside the sustainability commitments that many universities have made publicly. For institutions in LAC, a region that contributes disproportionately little to the technology producing these emissions while bearing a disproportionate share of climate risk, the adoption of AI tools without attention to environmental governance represents a tension that deserves explicit institutional acknowledgement (UNEP, 2024). It should be equally noted that AI offers transformative potential for environmental solutions. Higher education must lead in resolving AI's sustainability paradox, pioneering leaner architecture and efficient computing to ensure its transformative potential outweighs its growing environmental costs (United Nations University, 2025).

2.6 Epistemic and cultural homogenization

Beyond the question of individual bias in AI outputs, there is a broader concern: that the widespread adoption of AI tools trained on dominant, predominantly English-language and Western-

centric knowledge traditions, may gradually narrow what counts as legitimate knowledge in educational settings. As AI becomes embedded in teaching and research, the authority to define knowledge risks shifts from educators and institutions to the companies that own the technology, hollowing out epistemic governance as a public responsibility (Lindebaum et al., 2025). This has been framed in terms of *epistemicide* (the systematic sidelining of non-Western knowledge systems), and is a warning that AI's homogenizing tendencies may amplify existing power asymmetries in higher education (Omodan and Marongwe, 2024). In fact, AI-generated content has been shown to replicate cultural and linguistic biases, which students may unknowingly reproduce in their work, and that the overuse of generative AI tools risks undermining progress made in curriculum decolonization (Jose et al., 2025). For universities in LAC with explicit mandates to engage with and serve diverse, historically marginalized communities, these concerns speak directly to their mission.

2.7 Changing role of faculty

The integration of AI into teaching, assessment and research raises questions about the evolving role of academic staff and, for some, about the value of their professional expertise. A review of faculty perceptions across multiple studies found that AI is altering how educators allocate their time and define their professional responsibilities, shifting them from knowledge transmitters toward facilitators in AI-enhanced environments (Buele and Llerena-Aguirre, 2025). This transition has been accompanied by documented anxieties about deskilling, loss of autonomy and potential displacement, especially in administrative roles (Buele and Llerena-Aguirre, 2025; Klimova and Pikhart, 2025). Faculty resistance to AI adoption is frequently rooted in these concerns and should be understood as a genuine professional concern rather than dismissed as a reluctance to change.

2.8 Commercialization and dependency on private providers

Most AI tools available to higher education institutions are products developed by private technology companies whose commercial incentives do not necessarily align with public educational values. Institutions embedding AI into teaching and research systems are ceding part of their epistemic governance to private actors and this dependency carries risks of data sovereignty and the subordination of pedagogical decisions to commercial logic (Lindebaum et al., 2025). This concern is particularly important in LAC where constrained public budgets and limited technological infrastructure may make institutions more reliant on external providers and less able to develop or enforce their own standards. Encouraging the development of open, transparent and publicly governed AI tools rather than exclusive reliance on commercial platforms is increasingly discussed as both an ethical imperative and a strategic necessity (UNEP, 2024; UNESCO, 2022).

Before institutions move to scale AI integration, these concerns deserve serious engagement rather than retrospective acknowledgement.

3. Patterns of AI adoption

AI is entering universities in LAC but its adoption is neither uniform nor evenly distributed across dimensions. The findings from this survey reveal a hierarchy of adoption with teaching and learning emerging as the primary entry point for AI in the region's universities, followed by research, administration and community engagement (**Figure 5**).

3.1 Teaching and learning

AI adoption is most widespread in the region in the area of teaching and learning with 74 per cent of institutions reporting current use, a rate broadly consistent with global trends. The 2025 UNESCO survey of Chairs and UNITWIN Networks across 90 countries similarly found that nearly half of the 400 respondents were already experimenting with AI in teaching, including lesson planning and grading support, reinforcing the picture of teaching and learning as the primary site of AI integration in higher education worldwide (UNESCO, 2025).

Adoption rates in the region vary across institution types, with private non-profit universities showing the highest levels of use at 84 per cent, compared to 68 per cent for public institutions and 52 per cent for private for-profit institutions (**Figure 6**).

Figure 5. AI usage per type of function overall (Percentage, n=200)

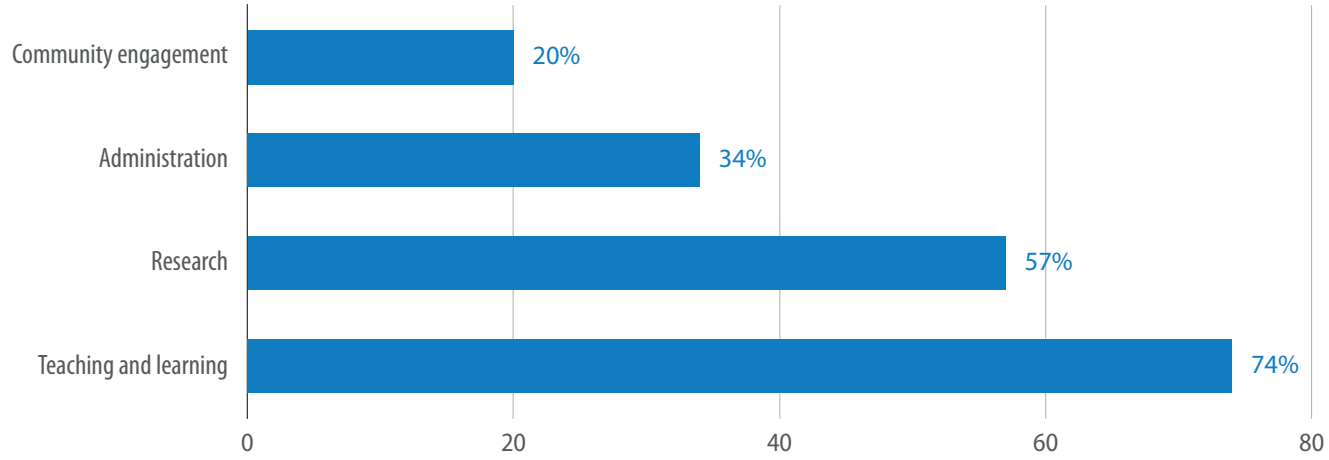
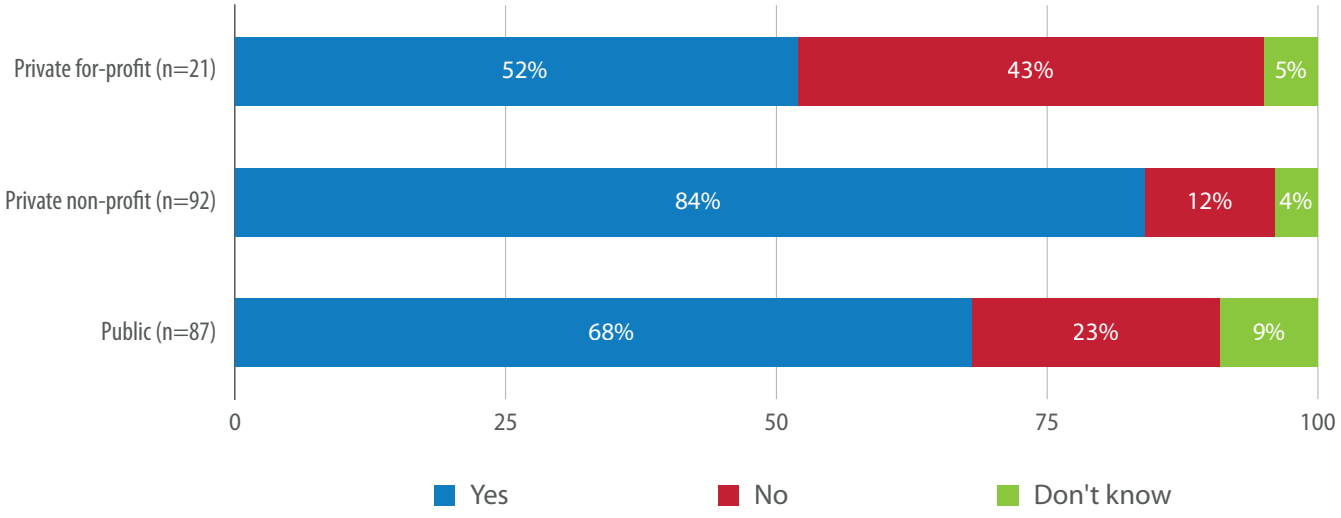


Figure 6. AI use in teaching and learning by institution type (Percentage)



Considering academic orientation, adoption rates in teaching and learning are similar across the three groups: multidisciplinary (74 per cent), polytechnic (75 per cent) and specialized (70 per cent) universities all cluster within five percentage points of each other. This is one of the few areas in the survey where academic orientation produces no meaningful difference, suggesting that the penetration of AI in teaching and learning has been sufficiently broad and accessible to reach all institutions regardless of their academic orientation (**Figure 7**).

The technology landscape is dominated by generative AI. Among universities using AI in teaching, 90 per cent report using tools such as ChatGPT, Copilot or Gemini, a rate that is uniform across all institution types. This finding resonates with global evidence as generative AI tools have seen particularly rapid uptake among students and faculty in higher education, especially for writing, research and course preparation tasks (UNESCO IESALC, 2023). This could suggest that generative AI has become the default entry point for AI adoption in teaching and learning across the region, likely driven by the free or low-cost availability of these tools and their ease of use without the need for significant institutional infrastructure (**Figure 8**).

Figure 7. AI use in teaching and learning per academic orientation (Percentage)

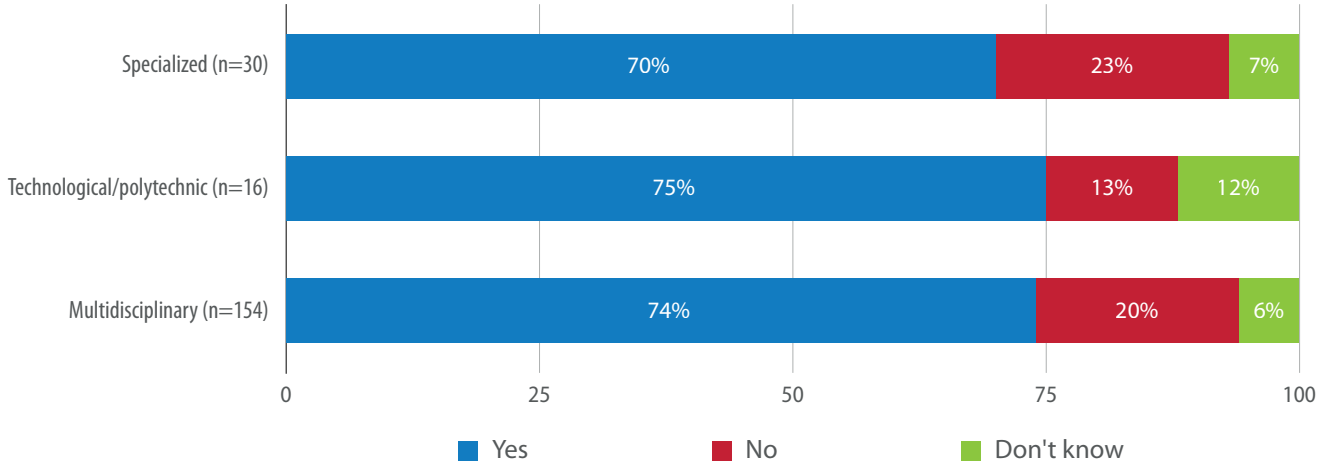
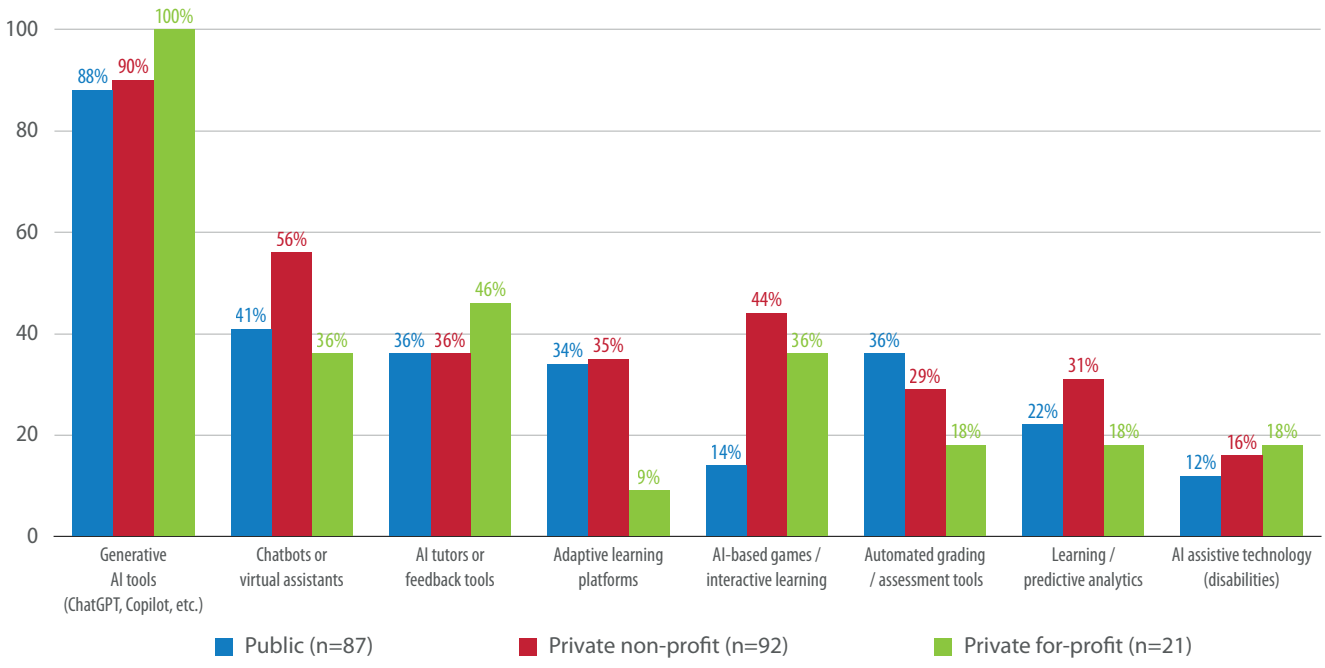


Figure 8. Types of AI technologies used in teaching and learning by institution type (Percentage)



In terms of academic orientation, the technology in teaching shows some variation beneath the surface uniformity of adoption rates. Generative AI tools dominate across all three groups – multidisciplinary (90 per cent), polytechnic (92 per cent) and specialized (86 per cent) – confirming that this technology has penetrated all institutional types equally. However, differences emerge if we consider other tools. Chatbots and virtual assistants are widely used by multidisciplinary (54 per cent) and polytechnic universities (58 per cent), but rarer among specialized institutions (14 per cent). Similarly, AI tutors and feedback tools are used by 43 per cent of multidisciplinary universities but only 10 per cent of specialized ones. This pattern could suggest that beyond generative AI, specialized universities are not investing in purpose-built pedagogical AI applications. Polytechnic universities stand out for their comparatively high use of adaptive learning platforms (42 per cent) and AI assistive technology for students with disabilities (33 per cent) (**Figure 9**).

When the objectives for AI use in teaching and learning are considered, the general option to *Promote pedagogical innovation* is the most frequently cited (71 per cent) followed by a group of concrete teaching and learning goals: *Improve teaching quality* (60 per cent), *Improve learning outcomes* (54 per cent), *Increase student engagement* (51 per cent) and *Reduce teacher workload* (50 per cent). Taken together, these top five objectives suggest that AI adoption in the classroom is driven by educational intent rather than by institutional positioning alone (**Figure 10**).

The lower-ranked objectives add further detail. Overall, *Personalize learning pathways* (41 per cent), *Automate grading and feedback* (30 per cent), *Support early identification of at-risk students* (27 per cent) and *Expand access and inclusion* (27 per cent) are cited by fewer than a third of institutions. This suggests that while the broad pedagogical intent is present, the more transformative and equity-oriented applications of AI in teaching remain underdeveloped.

If the objectives considering the academic orientation of the institutions are broken down, it is of note that the most considerable difference is in improving learning outcomes: multidisciplinary universities cite this at 58 per cent compared to just 33 per cent for polytechnic institutions. Conversely, *Improve teaching quality* (67 per cent) and *Increase student engagement* (58 per cent) rank higher for

Figure 9. Types of AI technologies used in teaching and learning by academic orientation (Percentage)

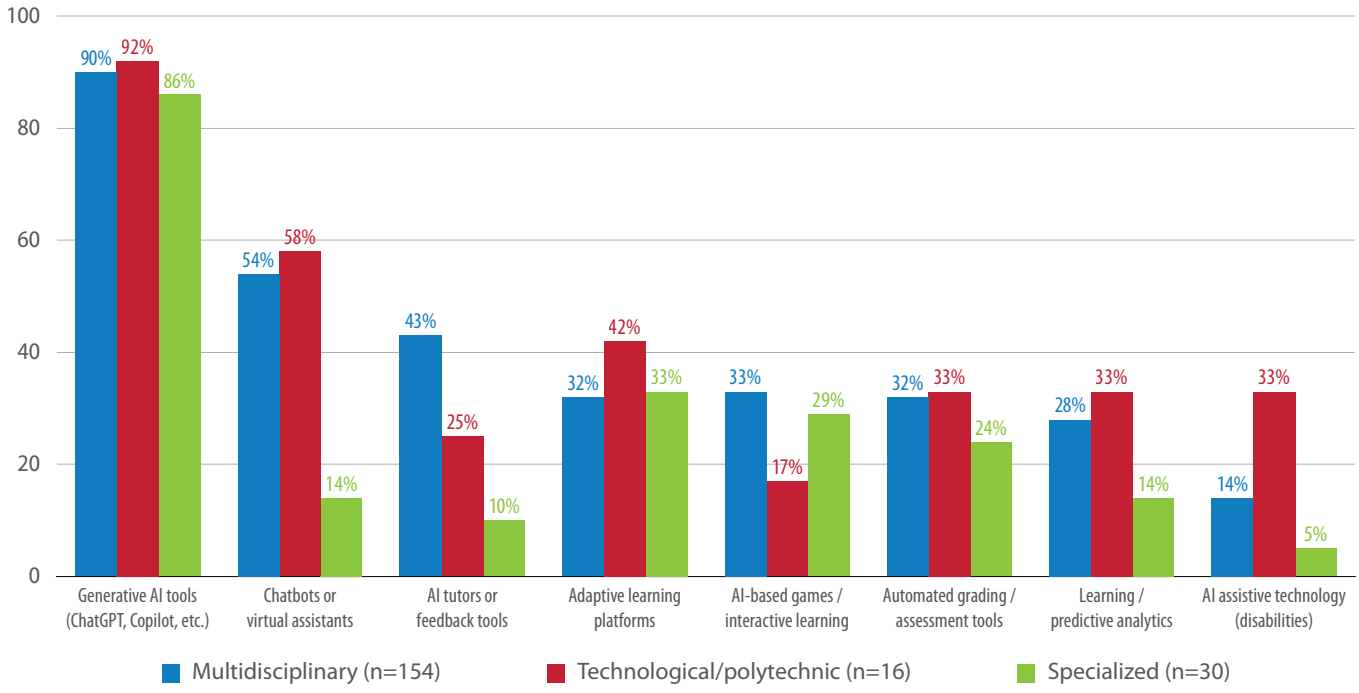


Figure 10. Overall objectives for AI use in teaching and learning (Percentage, n=200)

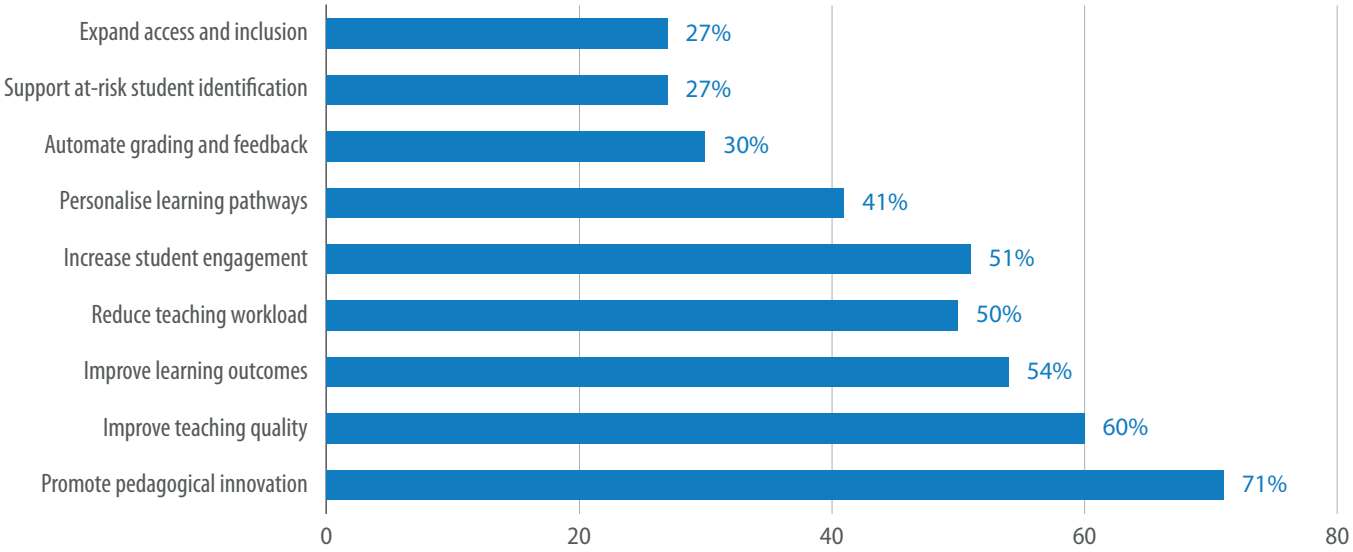
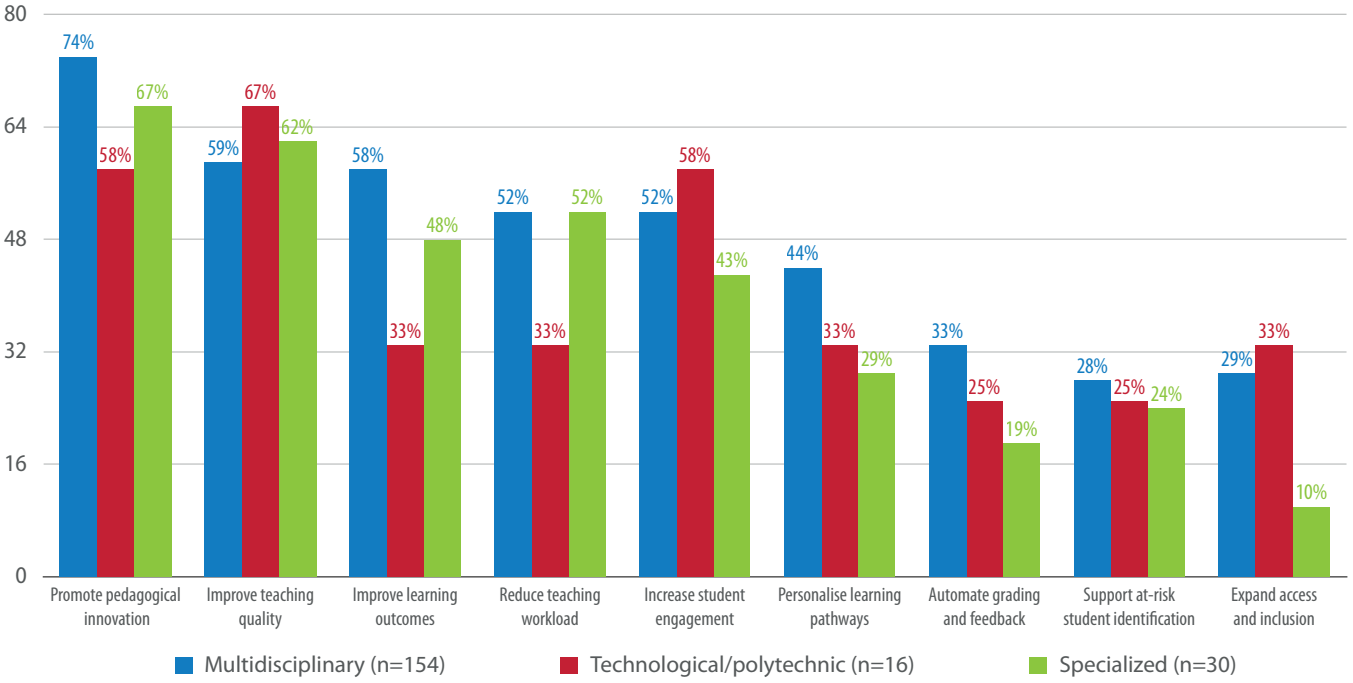


Figure 11. Objectives of AI use in teaching per academic orientation (Percentage)



polytechnic institutions, which could suggest a more practice-oriented, hands-on learning than the theory-based academic framing of AI in teaching (**Figure 11**).

3.2 Research

AI adoption in research is lower than in teaching and learning with 57 per cent of universities reporting its use. However, the high proportion of 'don't know' responses (23 per cent) is significant. Given that this survey was directed at senior institutional leaders, a response of 'don't know' to a question about AI in research suggests that in many universities, AI may be adopted at the level of individual researchers or groups and below the strategic radar of institutional leadership.

The distribution of 'don't know' responses is broadly uniform across institution types including public (24 per cent), private non-profit (22 per cent) and private for-profit (19 per cent). This suggests the

visibility gap is a systemic or sectoral feature of how AI adoption is currently spread across research rather than a problem concentrated in any institutional category (**Figure 12**).

The institutional type breakdown is broadly similar; however, the academic orientation breakdown reveals a different picture. Multidisciplinary universities report the highest adoption (60 per cent), followed closely by polytechnic institutions (56 per cent), while specialized universities have the lowest adoption rate at 43 per cent.

AI tools for literature synthesis, data analysis and writing support have seen rapid uptake among researchers, with applications including automated literature reviews, identification of trends and gaps across large bodies of scientific literature, and assistance with data analysis and visualization, all of which are particularly relevant in contexts such as LAC where access to research support infrastructure remains uneven (Molina and Medina, 2025).

Among the 114 universities that do report AI use in research, the objectives are generally practical and efficiency-oriented. *Accelerate data processing and analysis* (69 per cent), *Improve research quality* (65 per cent) and *Improve literature review efficiency* (64 per cent) dominate. These are followed by *Reduce repetitive tasks* (45 per cent) and *Enable larger-scale research projects* (39 per cent) (**Figure 13**).

3.3 Administration

AI adoption in administrative functions is reported by just over a third of surveyed institutions (34 per cent) making it less common than in teaching and learning or research and is accompanied by the highest 'don't know' rate in the survey at 29 per cent. In a survey directed at senior institutional leaders, this figure carries analytical weight as more than one in four university leaders cannot confirm whether AI is being used to run their institution's own administrative operations. This could point to a dynamic in which AI tools are adopted at the departmental or operational level without the knowledge or oversight of institutional leadership. It could also reflect an ad hoc use of AI for basic tasks such as editing and drafting, where staff do not perceive themselves as using it in any formal or consequential sense.

The pattern is consistent with both the historical tendency for technology adoption to precede institutional oversight (Palvia et al., 2018) and

Figure 12. AI use in research per academic orientation (Percentage)

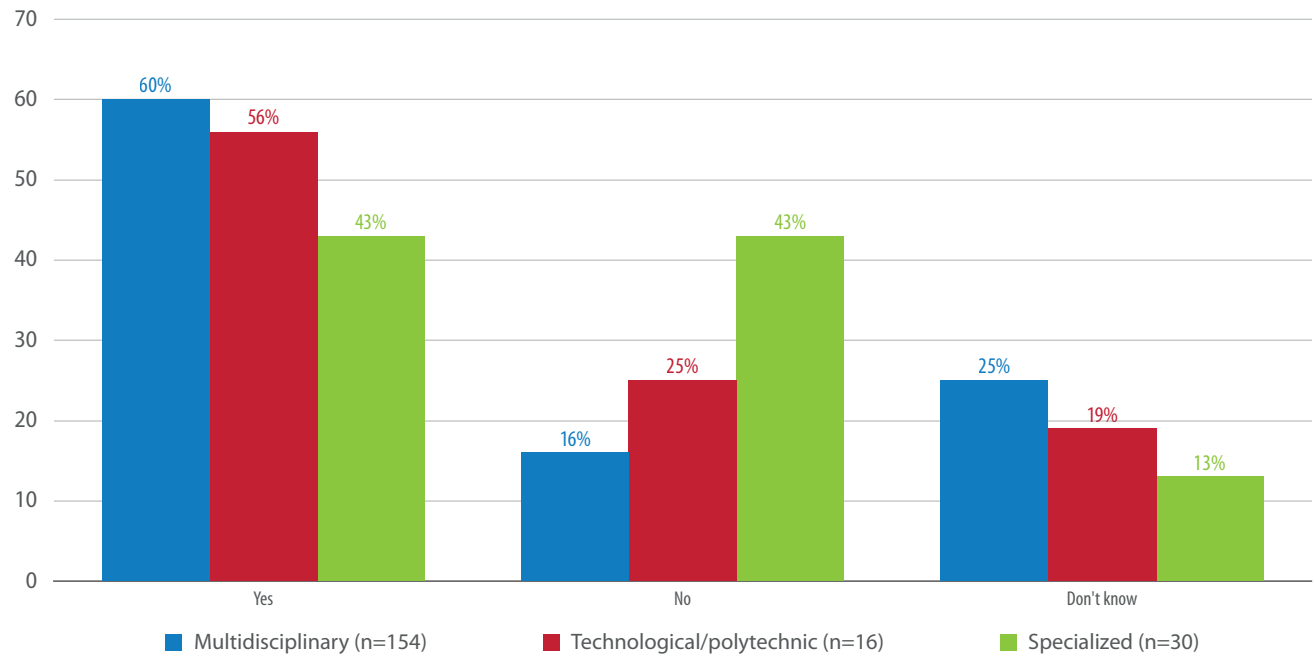


Figure 13. Overall objectives for AI use in research (Percentage)

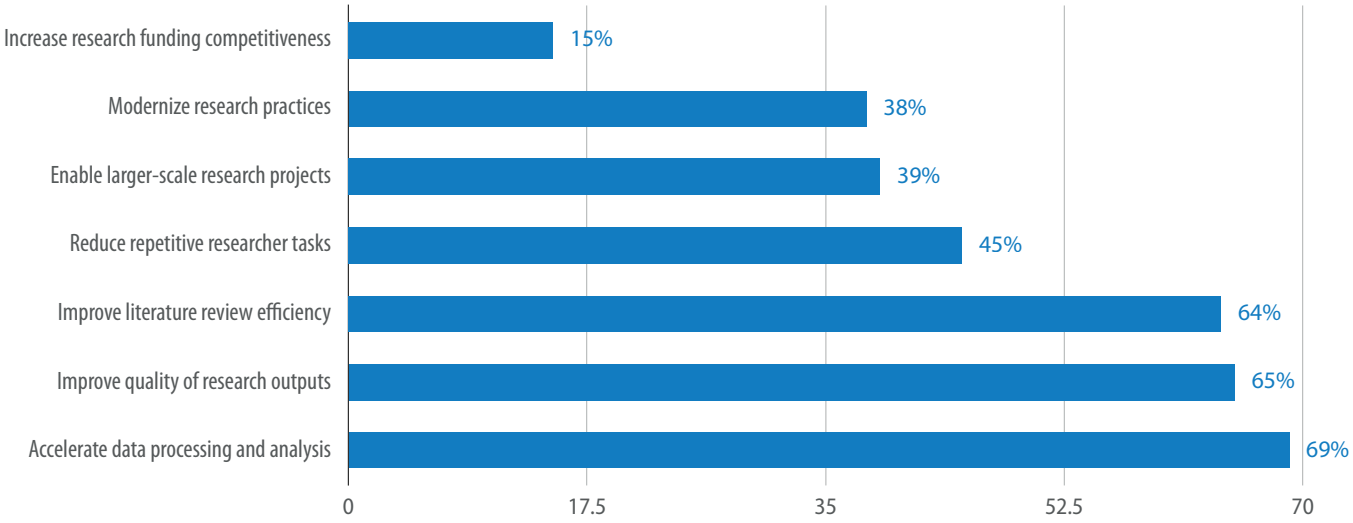
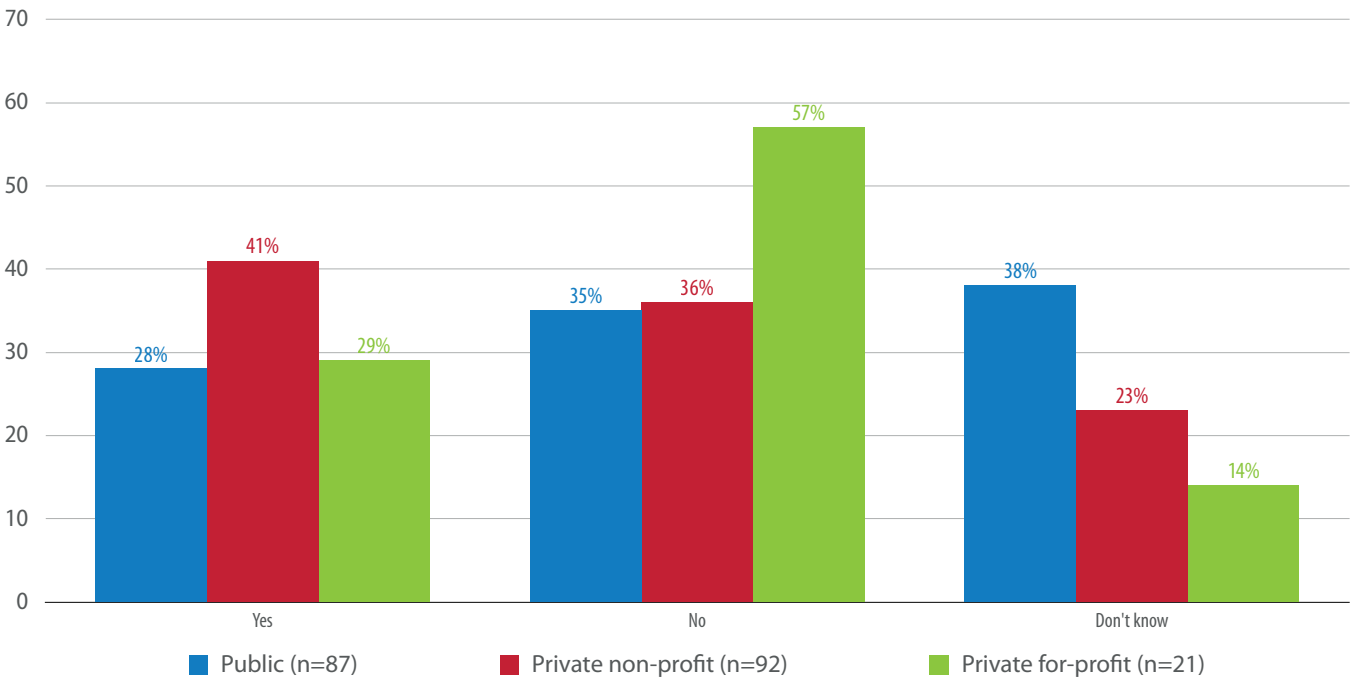


Figure 14. AI use in administration per institutional type (Percentage)



the specific governance challenges documented throughout this report. What makes administrative AI particularly difficult to manage responsibly is that the data it processes (student performance, behaviour, financial records) carries significant accountability implications that ungoverned adoption at the operational level is poorly equipped to address. The 'don't know' rate is highest among public universities (38 per cent), compared to 23 per cent for private non-profit and 14 per cent for private for-profit institutions (**Figure 14**).

By academic orientation, the adoption is more differentiated than in teaching and learning. Specialized universities report the highest administrative AI adoption (50 per cent), above multidisciplinary institutions (33 per cent) and polytechnic universities (19 per cent). One plausible explanation is that smaller institutions may encounter lower barriers to deploying AI tools in specific administrative functions than larger institutions with more complex legacy systems and administrative structures (**Figure 15**).

Figure 15. AI use in administration per academic orientation (Percentage)

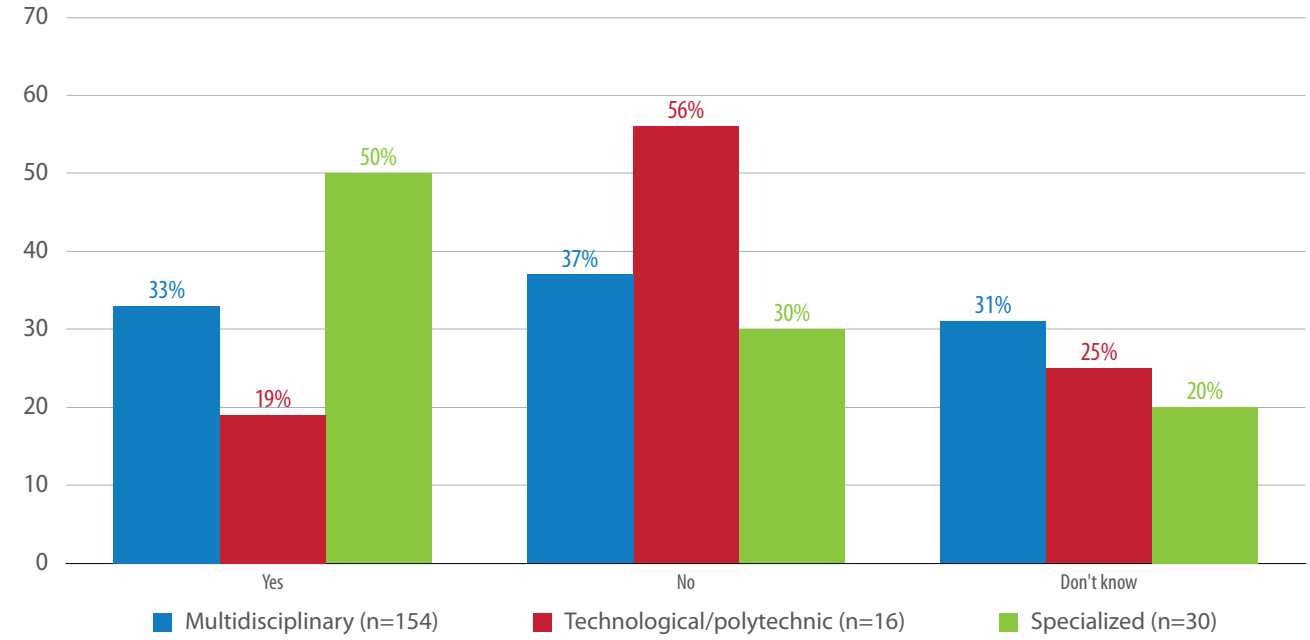
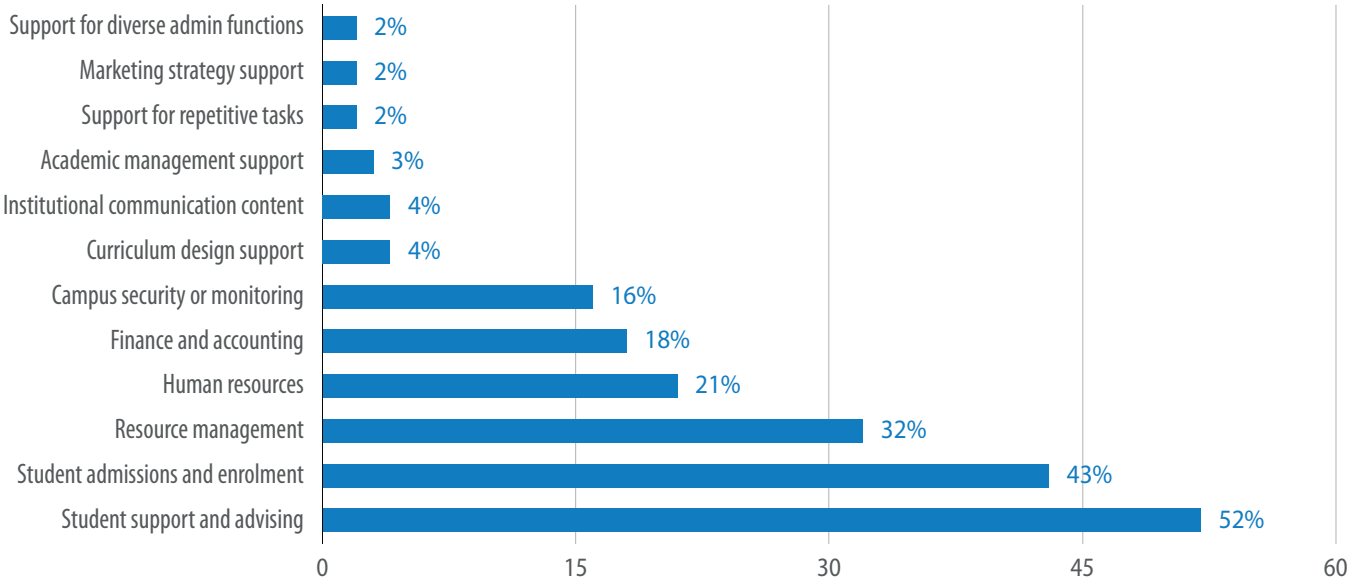


Figure 16. Overall administrative areas where AI is applied (Percentage)



Among the 68 universities reporting administrative AI use, the applications are concentrated in student-facing functions: *Student support and advising* (52 per cent) and *Admissions and enrolment* (43 per cent) are the two most common areas. AI-driven tools for identifying at-risk students – analysing data on behaviour, performance and participation to enable early intervention – are among the most well-evidenced administrative applications globally, with studies showing improvements in persistence and enrolment rates when such tools are well-designed and carefully implemented (Khairullah et al., 2025; Molina and Medina, 2025). At the same time, the use of AI for student-facing services can pose risks related to data privacy and algorithmic biases.

Resource management (32 per cent), *Human resources* (21 per cent) and *Finance and accounting* (18 per cent) are present but less developed, suggesting that the more operationally sensitive administrative functions remain largely outside the current scope of administrative AI in the region (**Figure 16**).

One notable difference by academic orientation: multidisciplinary universities are nearly three times more likely than specialized institutions to use AI in Admissions and enrolment (52 per cent vs. 20 per cent), which may reflect the higher volume and complexity of admissions processes in larger, broader institutions.

The objectives articulated for administrative AI are dominated by efficiency considerations. Automation of routine tasks is cited by 79 per cent, the most frequently cited objective – a finding consistent with observations across the literature on administrative AI adoption in higher education, which frequently identifies efficiency gains and workload reduction among the primary drivers of institutional uptake (Khairullah et al., 2025; Molina and Medina, 2025; UNESCO IESALC, 2023). *Reduce staff workload* (62 per cent), *Support data-driven decision-making* (56 per cent) and *Improve accuracy and speed of administrative processes* (50 per cent) complete the top tier (**Figure 17**).

3.4 Community engagement services

Community engagement records the lowest AI adoption rate of any functional area surveyed at 20 per cent, compared to 74 per cent for teaching and learning and 57 per cent for research. This pattern likely reflects a broader tendency to concentrate early AI integration in the academic core. It may also reflect something more substantive: community engagement is inherently relational, built on trust, local knowledge and direct human interaction with communities, thus the case for deep AI integration in this mission is less evident than in other domains. Whether lower adoption here represents a gap, a deliberate choice or simply a function of limited institutional visibility, is not clear from the survey data alone. The high 'don't know' rate (32 per cent) suggests that community engagement is the function furthest from senior leadership attention, which raises its own governance questions regardless of the level of AI involvement (**Figure 18**).

By institution type, private non-profit universities show the highest adoption rate (27 per cent) above public (14 per cent) and private for-profit institutions (14 per cent). The 'don't know' rate is highest among public universities (41 per cent), suggesting that AI adoption in community engagement is particularly invisible to senior leadership in the public sector. This may reflect the more decentralized nature of community engagement activities in larger public universities, where initiatives might be driven by individual faculties or departments rather than by institutional strategy (**Figure 19**).

By academic orientation, adoption is low across all groups: multidisciplinary (21 per cent), specialized (17 per cent) and polytechnic (13 per cent), and the subgroup sizes among users (n=33, n=5, n=2,

Figure 17. Overall objectives of AI use in administration (Percentage)

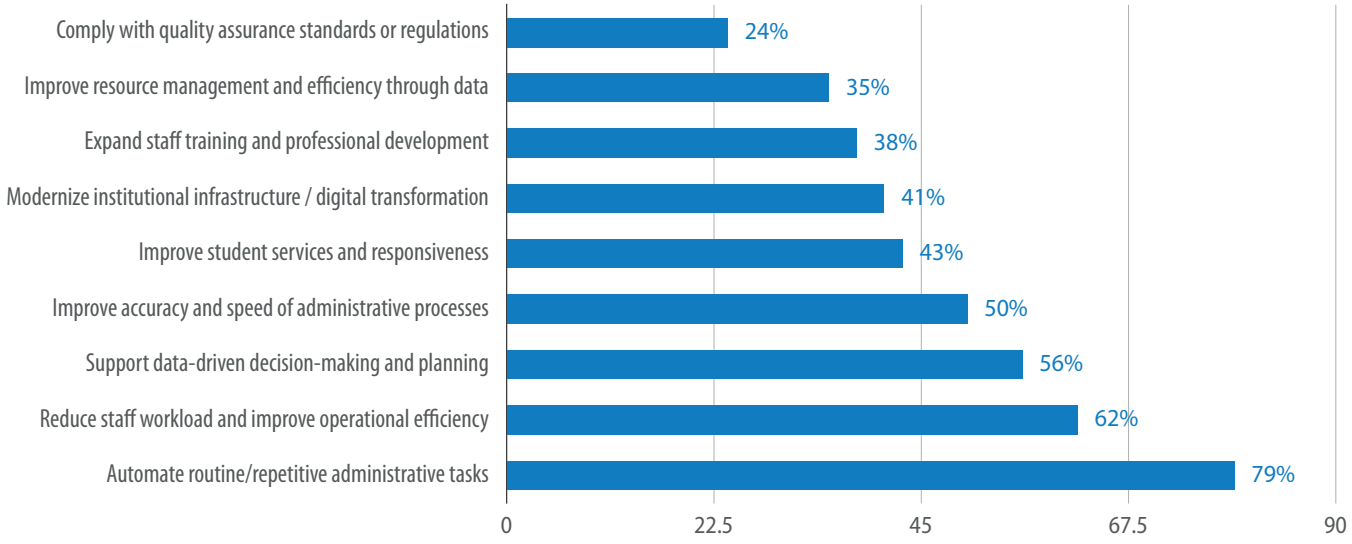


Figure 18. Overall AI adoption in community-facing services (Percentage)

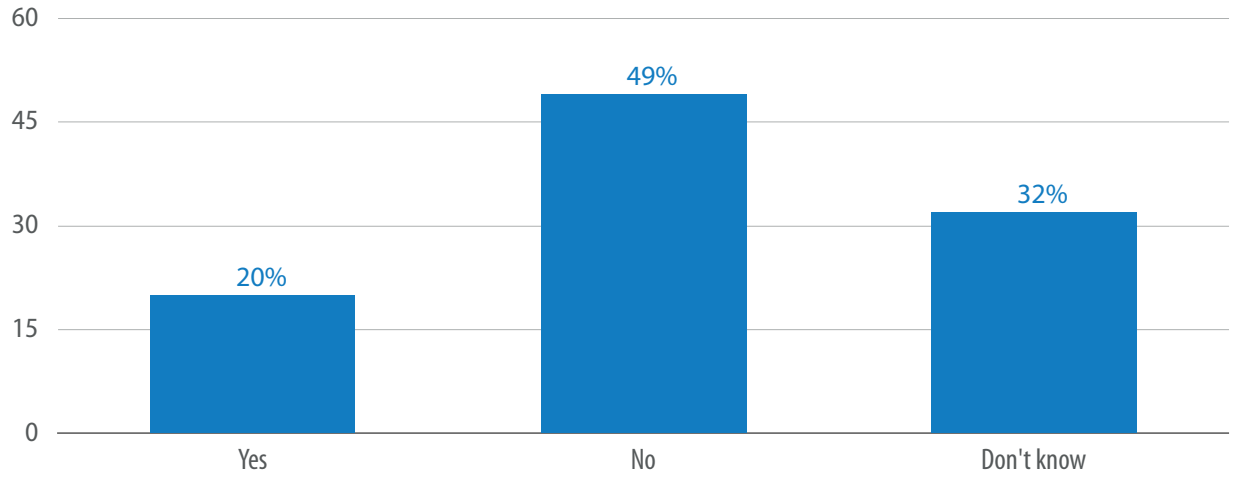
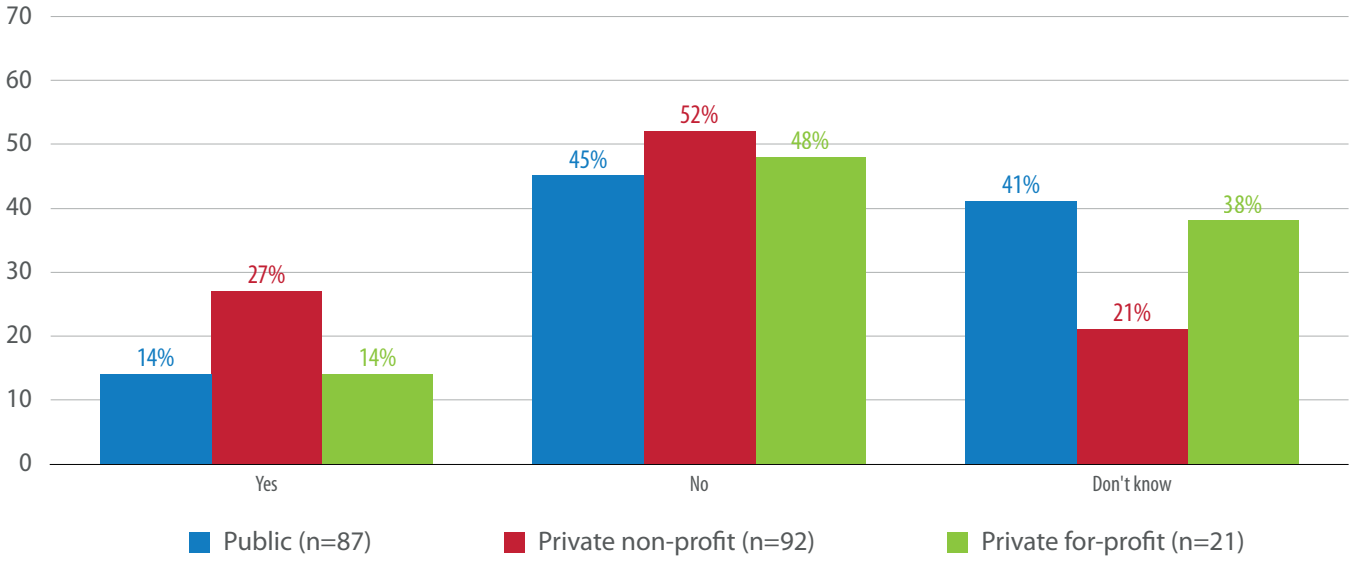


Figure 19. AI adoption in community-facing services per institutional type (Percentage)



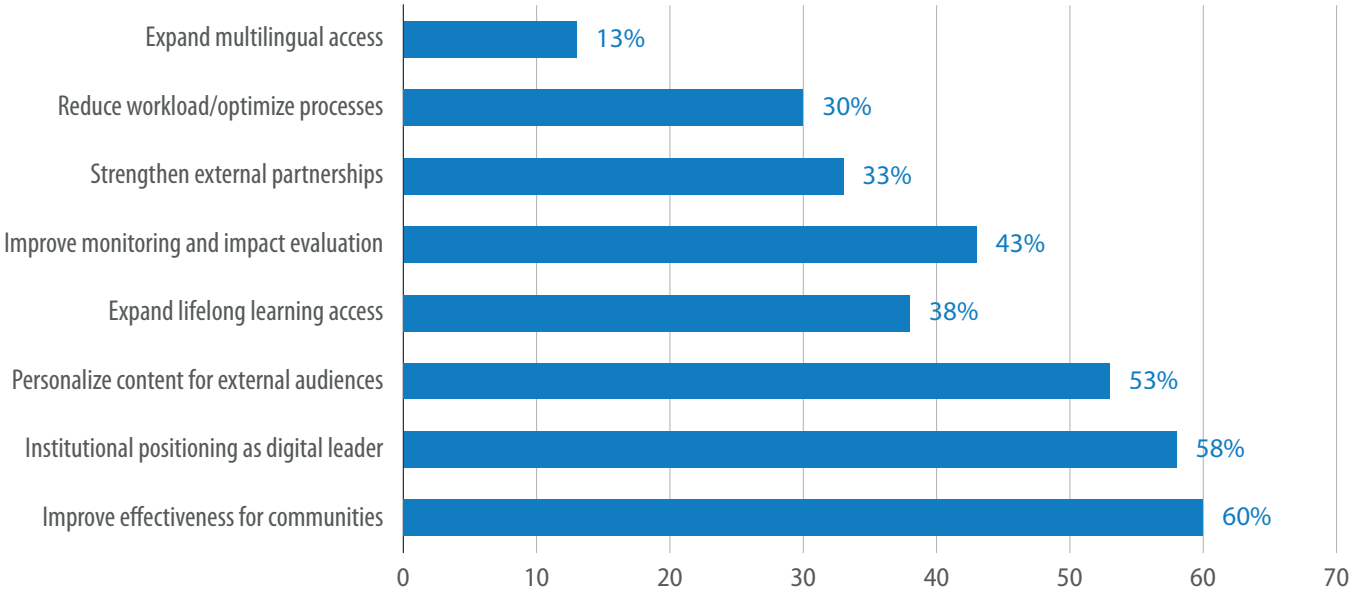
respectively) are too small to support meaningful breakdown.

Among the 40 universities that do report AI use in community engagement, *Improve effectiveness for target communities (*60 per cent) and *Institutional positioning as a digital leader* (58 per cent) are the most cited objectives, closely followed by *Personalize content for external audiences* (53 per cent). The near-equal presence of institutional positioning alongside community impact suggests that for some universities, AI in community engagement is partly a reputational strategy rather than a response to genuine community need, a distinction worth monitoring as adoption in this domain develops. Given the small base (n=40), all findings in this section should be interpreted with considerable caution, and the objectives breakdown by any subgroup does not add value (**Figure 20**).

3.5 Key findings

The findings across the three core missions and the administrative function document a hierarchy of AI adoption. A first pattern to emerge is that teaching and learning leads by a wide margin, with nearly three quarters of universities reporting AI use, compared with fewer reporting use in community engagement. Research and administration fall between these extremes at 57 per cent and 34 per cent respectively.

Figure 20. Overall objectives of AI use in community services (Percentage)



This suggests that generative AI tools entered universities primarily through the everyday work of teaching, learning and research, likely driven by the wide availability of accessible, low-cost tools rather than by deliberate institutional planning (Jin et al., 2025). Administrative and community engagement dimensions, which are more operationally bounded and less immediately shaped by the tools students and faculty encounter in their daily work, have followed at a distance. This pattern is consistent with what UNESCO IESALC has observed in previous work across more than 40 higher education institutions in the region: AI adoption in teaching and learning tends to follow a bottom-up dynamic, where students begin using AI tools for learning and assessments, faculty subsequently adapt their practices, and institutional governance responds by developing guidelines (UNESCO IESALC, 2025a).

A second pattern runs across all four dimensions: private non-profit universities report higher AI adoption rates than public institutions in every case. The gap, present throughout, is most pronounced in teaching and learning (84 per cent vs. 68 per cent) and administration (41 per cent vs. 28 per cent). This is important because public universities in many countries in the region carry broader social mandates, serving larger student populations, higher shares of students from lower-income backgrounds, and a greater responsibility for the democratization of higher education as a public good. A persistent and widening AI adoption gap between public and private institutions therefore could carry equity implications that extend beyond the universities themselves. In the absence of targeted policy intervention, students with the greatest structural need for the potential benefits of AI (personalized support, early intervention, reduced dropout) may be the least likely to access them through their institutions while simultaneously being more exposed to ungoverned AI use where institutional oversight is weakest.

4. Continuous professional development opportunities

The adoption of AI in universities affects those who teach, learn and work in these institutions, and it raises questions about how well-prepared they are to use these tools in a responsible manner. This section looks at the training opportunities that higher education institutions are providing to help staff and students navigate this new context.

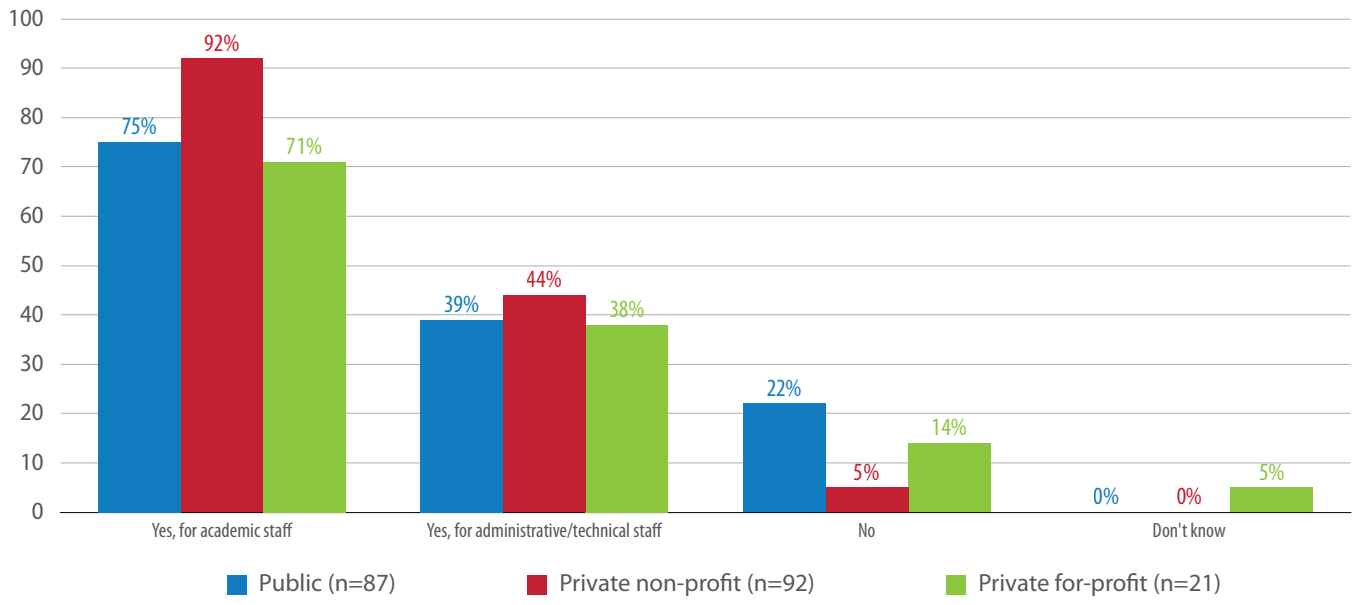
4.1 Training staff

The vast majority of universities (83 per cent) report having implemented AI training programmes for academic staff, suggesting that capacity development for teaching personnel in the context of AI has become relatively widespread across the region.

However, coverage drops when it comes to administrative and technical staff. Only 41 per cent report extending training to this group, revealing a significant gap in institutional approaches to AI readiness. Literature shows that AI literacy programmes in higher education have predominantly focused on academic and teaching staff with administrative staff systematically under-represented in capacity development efforts (UNESCO IESALC, 2023). Such lack of training opportunities for administrative staff may be a reason why the use of AI was less prevalent in administrative work than teaching and research, as shown in the previous sections. At the same time, this lack of training is problematic as staff using AI in operational contexts are less likely to have received training to use it responsibly.

Differences by institution type are notable. Private non-profit universities report the highest rates of academic staff training (92 per cent) while public universities (75 per cent) and private for-profit institutions (71 per cent) lag. This gap is consistent with what the literature identifies as a structural asymmetry in institutional AI readiness. Buele and Llerena-Aguirre (2025) find that faculty adoption patterns are mediated by institutional context, specifically the availability of structured training programmes and 'clear experimentation spaces', both of which are more likely to exist in better-resourced private institutions. The implication is that the training gap documented here is not simply a reflection of individual faculty attitudes but of different institutional investment in capacity development (**Figure 21**).

Figure 21. AI training for staff by institution type (Percentage)



By academic orientation, differences in staff training coverage are equally notable. Polytechnic universities report the highest rate of AI training for academic staff (88 per cent), followed by multidisciplinary (84 per cent) and specialized universities (70 per cent). The disparity is even more pronounced for administrative and technical staff: multidisciplinary (44 per cent) and polytechnic universities (44 per cent) extend training to this group at similar rates, while only 23 per cent of specialized universities do so. Specialized universities also show the highest rate of no training at all (27 per cent) (**Figure 22**).

Together these figures reinforce the picture of specialized universities as the group most at risk with the most limited institutional infrastructure for engaging with AI.

4.2 Training students

AI training for students is less widespread than for staff, and the modalities through which it is delivered vary. The figures reported in this study reflect institutionally organized or curricularly embedded training as perceived by senior leaders. They do not capture course-specific AI guidance that individual faculty may provide independently, which may be considerably more widespread. With this important caveat in mind, the most common institutionally recognized approach is the elective course model (41per cent), followed by curriculum integration (34 per cent). Some 35 per cent of universities report no centrally organized or formally embedded student AI training of any kind.

The prevalence of the elective model over full curriculum integration may suggest that many universities are at an early stage, offering AI courses as an option rather than as a core competency embedded across programmes. This runs counter to recommendations in the literature, which emphasize that AI literacy requires the embedding of AI not as a standalone subject but as a transversal competency across disciplines (Jaramillo and Chiappe, 2024) (**Figure 23**).

By institution type, private non-profit universities are the most likely to have integrated AI into the curriculum (42 per cent), while public universities show the highest share reporting no training (40 per cent).

This pattern reflects a broader global divide. The Digital Education Council's global AI student survey found that 86 per cent of students already use AI tools in their learning (Digital Education Council, 2024). This suggests that the absence of formally recognized or centrally organized training does

Figure 22. AI training for staff by academic profile (Percentage)

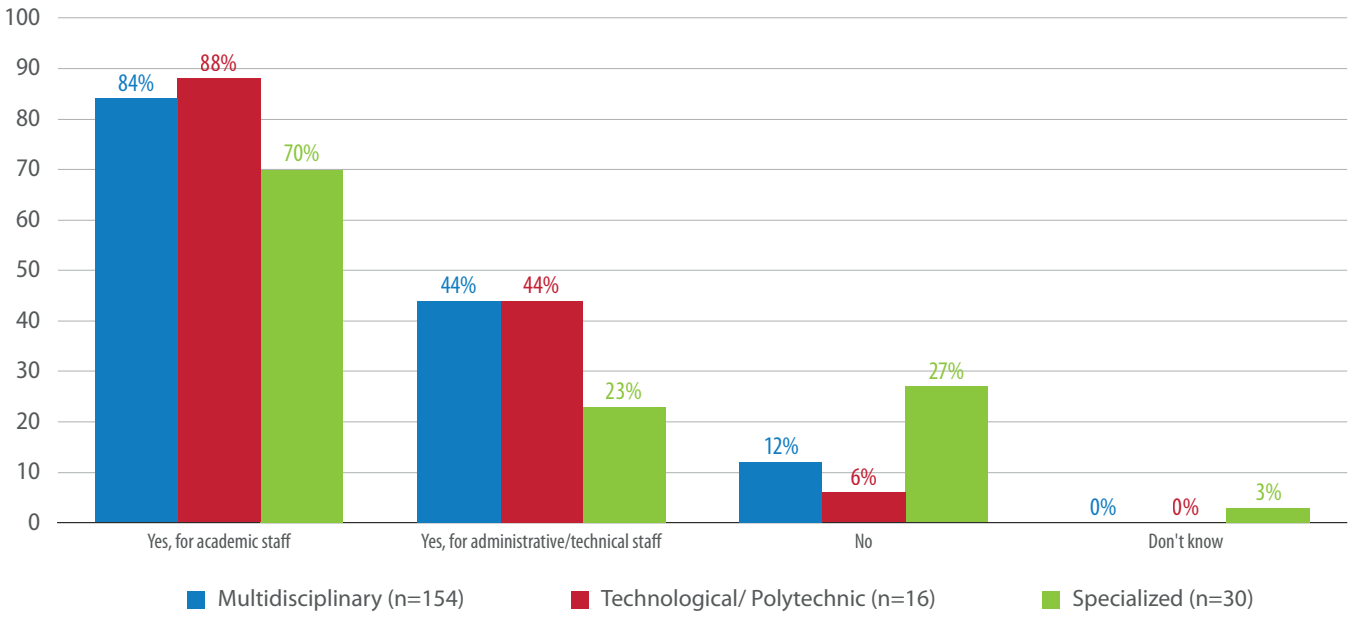


Figure 23. AI training for students by institution type (Percentage)

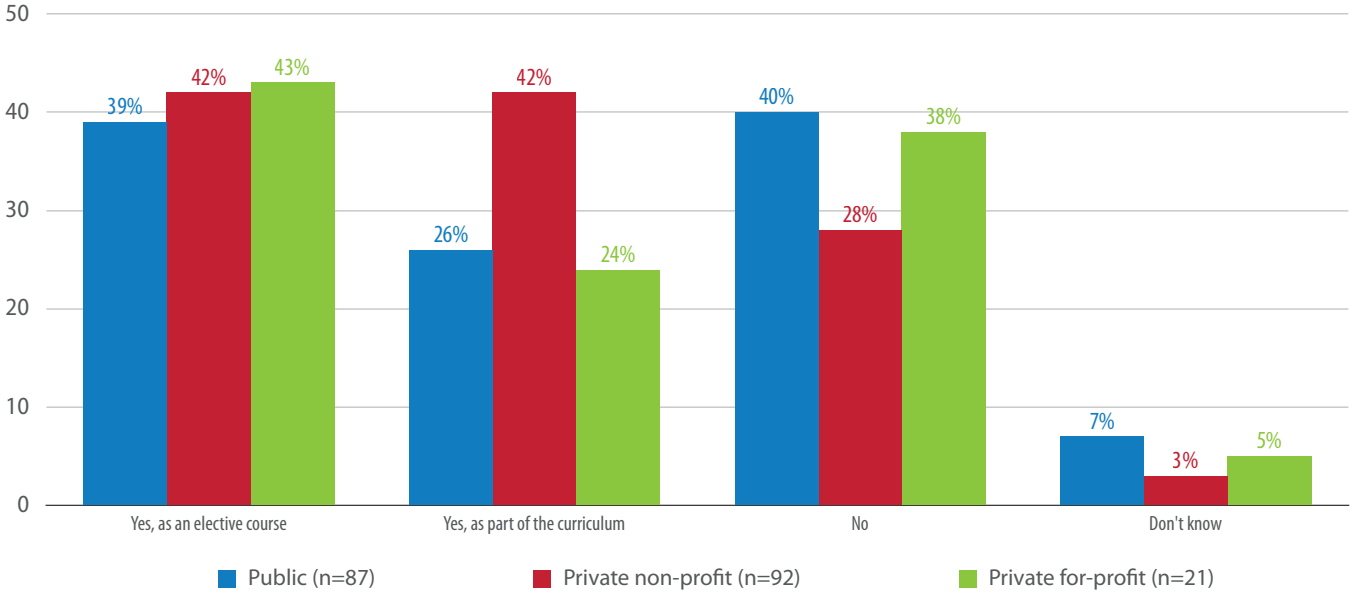
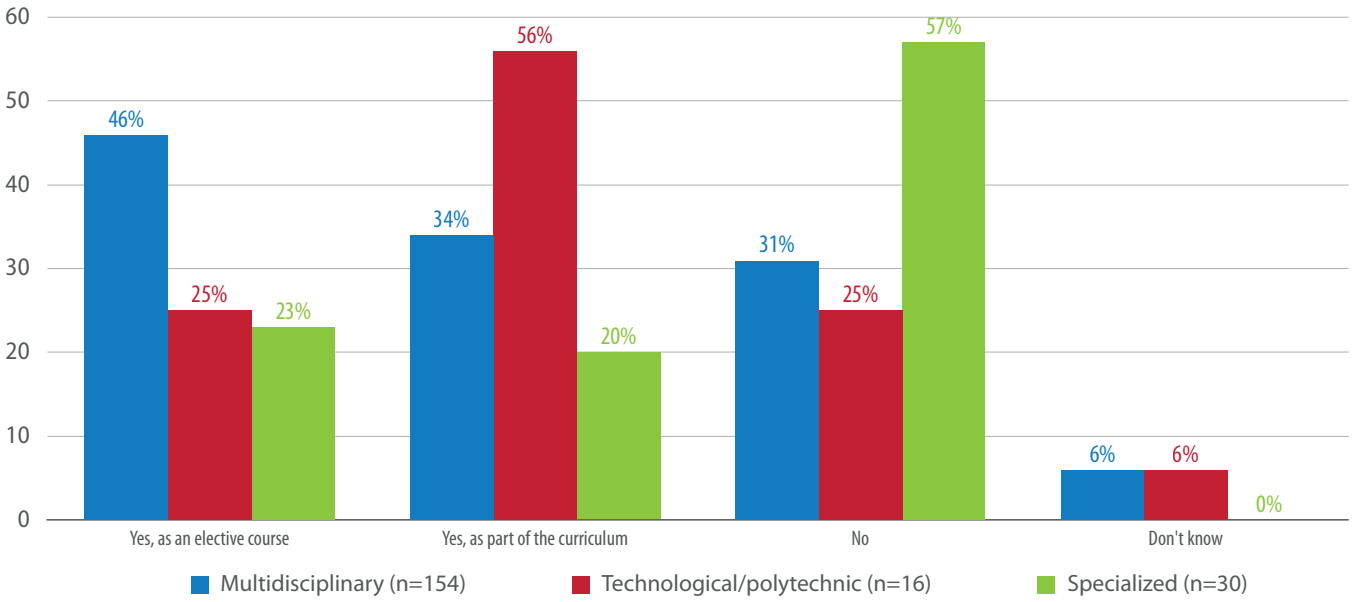


Figure 24. AI training for students by academic profile (Percentage)



not prevent student use. However, it does raise questions about whether that use is accompanied by adequate institutional guidance, ethical framing or pedagogical scaffolding, whether delivered through the formal curriculum or at the level of individual courses. The most interesting finding by university type is the contrast between polytechnic and specialized institutions. Polytechnic universities report the highest rate of curriculum integration (56 per cent), while specialized universities show the lowest rates of any training modality and the highest share reporting no student AI training (57 per cent). This divergence may partly reflect differences in institutional mission: polytechnic universities are generally characterized by a stronger practical and labour market orientation than other institution types, which may make them more attuned to emerging skill demands such as AI literacy and AI job-specific skills (Kyvik, 2004). The particularly low training rates among specialized universities, however, remain difficult to explain from the survey data alone. It is possible that course-level AI guidance exists within these institutions but is not captured by a survey directed at senior leaders. Further investigation at faculty and programme level is needed to draw firmer conclusions (**Figure 24**).

4.3 Training gaps among universities using AI in teaching and learning

Among the 147 universities that report using AI in teaching and learning, 8 per cent have no academic staff training programme in place and 25 per cent offer no student training of any kind. These figures deserve attention as they showcase universities that have already made the decision to use AI in their classrooms but have not taken steps to prepare either their staff or their students to engage with it responsibly and effectively.

By institution type, the staff training gap is mostly concentrated in the public sector. Among public universities using AI in teaching (n=59), 17 per cent have no academic staff training, almost six times the rate of private non-profit universities in the same group (3 per cent), and higher than the overall average of 8 per cent. Private for-profit universities using AI in teaching report no cases of absent staff training, suggesting that where these institutions have committed to AI adoption in the classroom, they have backed it with staff capacity development. The student training gap tells a more uniform story across institution types: 25 per cent of public, 25 per cent of private non-profit and 18 per cent of private for-profit universities using AI in teaching offer no student training. The gap is smallest among private for-profit institutions, consistent with their generally stronger student-facing accountability, but no institution type is free of this gap (**Figure 25**).

By academic orientation, the staff training gap is similar across groups: multidisciplinary (8 per cent), polytechnic (8 per cent) and specialized (10 per cent) universities show comparable rates of absent staff training among AI users. The student training gap, however, diverges sharply. Specialized universities using AI in teaching show by far the highest rate of no student training at 43 per cent, meaning that nearly half of specialized universities deploying AI in their classrooms are not providing students with any formal training to understand or use it. This is more than double the rate of multidisciplinary institutions (22 per cent) and nearly three times that of polytechnic universities (17 per cent). This finding is analytically significant as it can suggest that in specialized universities, AI adoption in teaching is largely a staff-level and tool-level decision that has not yet been extended to a broader educational strategy for developing students' AI competencies. Given that specialized institutions often train students for specific professional fields – health sciences, teacher education, business – the absence of student AI preparation carries consequences that could extend beyond the university into the labour market (**Figure 26**).

The training gap observed resonates with findings beyond the region. The Digital Education Council

Figure 25. Students and staff with no training among universities using AI in teaching and learning per institution type (Percentage, n=147)

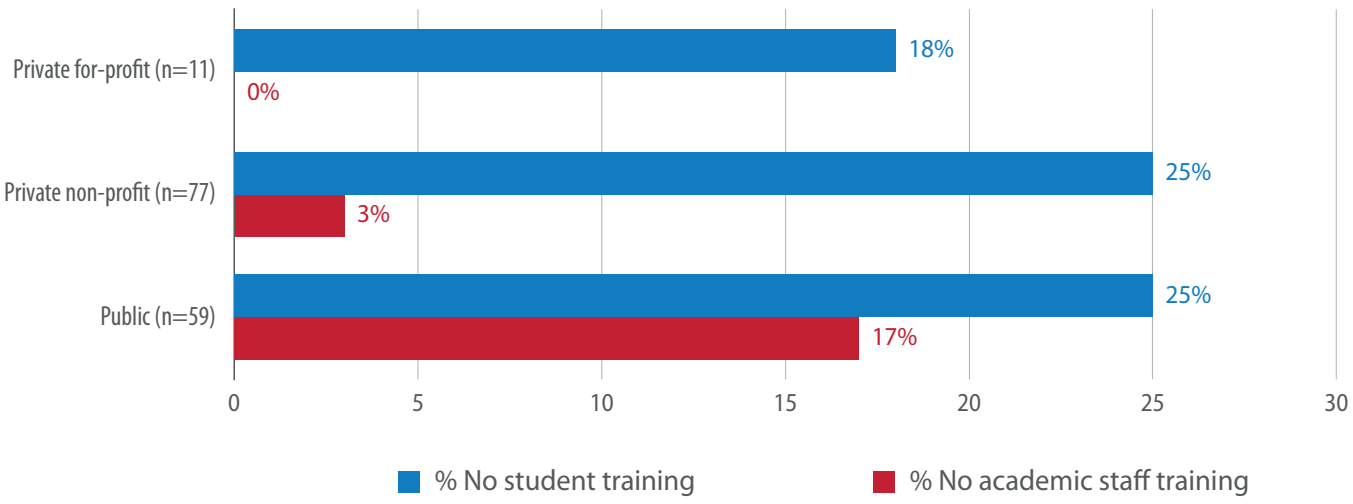
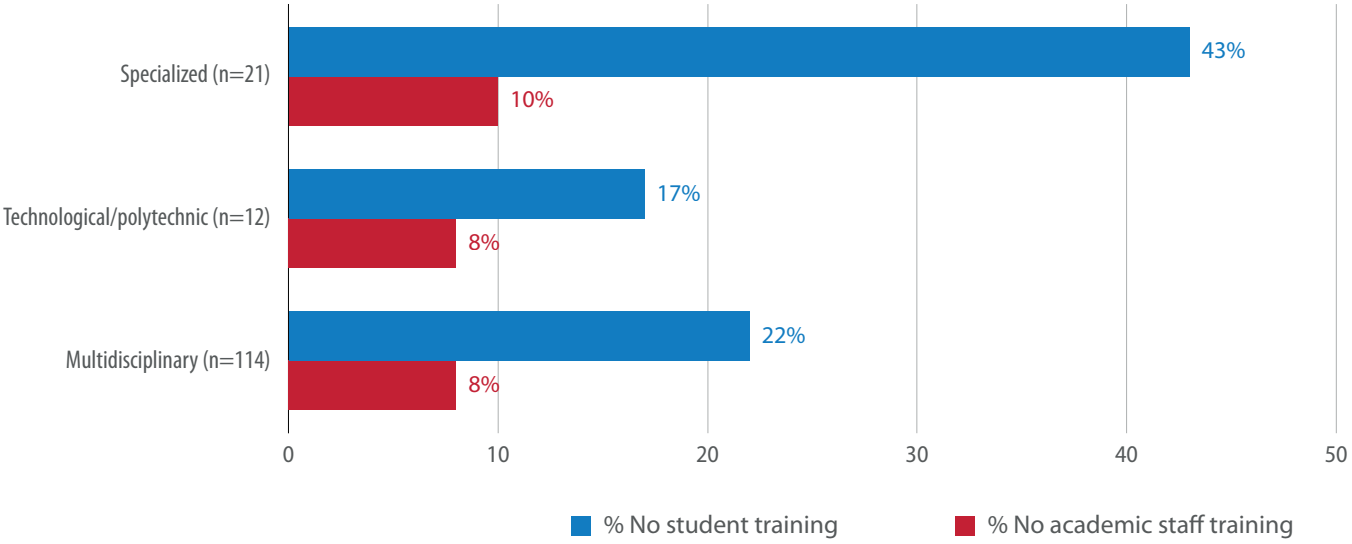


Figure 26. Students and staff with no training among universities using AI in teaching and learning per academic orientation (Percentage, n=147)



Faculty Survey, for example, found that 78 per cent of faculties across 28 countries do not consider their institutions to have provided sufficient resources for developing AI literacy, with only 6 per cent fully satisfied with available support (Digital Education Council, 2025). This confirms that the gap between the pace of AI adoption and institutional investment in training is a shared challenge.

5. Institutional readiness and governance

Across universities in the region, AI tools are being introduced faster than the institutional frameworks designed to govern them. This is not a new phenomenon. Higher education institutions have historically adopted successive waves of technology, from computers and the internet to learning management systems and massive open online courses, before developing the governance, policy and pedagogical frameworks needed to manage them responsibly (Feng et al., 2025; Palvia et al., 2018). Governance responses have consistently followed adoption rather than preceded it. Understanding the current AI governance gap in this historical context is important as it reframes what might appear as institutional failure as a structurally familiar pattern, one in which motivated individuals and early adopters drive initial uptake while institutional routines, policies and accountability structures gradually catch up (Isaifan, 2026; Jin et al., 2025).

What distinguishes AI from previous technology, however, is the speed, scale and depth of its penetration into core academic functions and the complexity of the risks it introduces from algorithmic bias and data privacy to academic integrity and epistemic dependency. These features make the governance lag more consequential than before and strengthen the case for an accelerated institutional response.

The findings presented in this section should be read both as evidence of a historically familiar pattern and as a sign that the sector cannot afford to wait as long as it did with previous technologies and that the gap has measurable consequences. As mentioned in the previous section, among the 147 universities that report using AI in teaching and learning, 8 per cent have no academic staff training in place and 25 per cent offer no student training of any kind, meaning that a significant share of institutions are deploying AI in the classroom without having prepared either those who teach with it or those who learn through it.

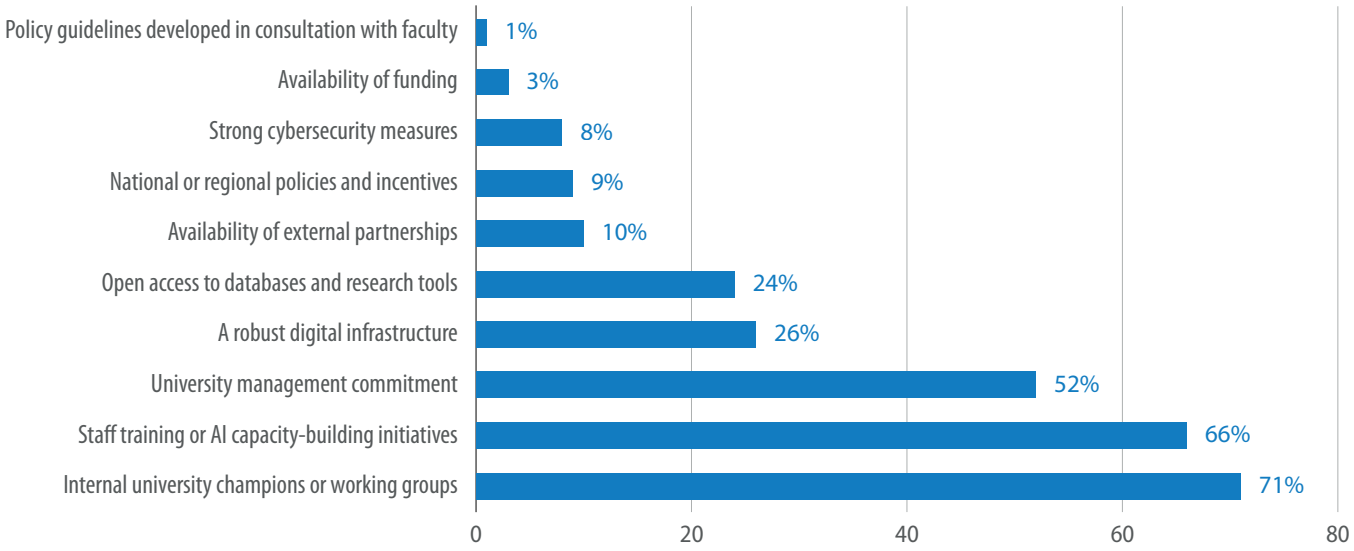
Before delving into institutional readiness, it is worth noting the structural context in which these findings sit. As specified in section 1.1, the sample is predominantly composed of multidisciplinary universities across all institution types: 72 per cent of public, 80 per cent of private non-profit and 81 per cent of private for-profit universities fall into this category. Institution size varies considerably, with public universities tending to be large (41 per cent enrol more than 15,000 students) while for-profit and specialized institutions are predominantly small. These features shape the capacities documented throughout this section: governance gaps, budget deficits and policy underdevelopment are not evenly distributed but are systematically more acute in smaller and presumably more resource-constrained institutions.

When asked to identify what enables AI adoption at their institutions, university leaders pointed to people rather than resources or policy. *Internal university champions or working groups* (71 per cent), *Staff training or AI capacity-building initiatives* (66 per cent) and *University management commitment* (52 per cent) outpaced structural enablers such as *A robust digital infrastructure* (26 per cent), *Availability of external partnerships* (10 per cent) or *National or regional policy incentives* (9 per cent) (**Figure 27**).

This people-first picture of AI adoption could help explain both the relative progress and the relative fragility of the institutional AI landscape documented in this section. It appears that AI adoption in the region is being driven by motivated individuals operating within institutions that have not yet built the frameworks to sustain, govern or evaluate what those individuals are doing.

The training data documented in the previous section complement this picture in an important way. While 66 per cent of university leaders identify staff training or AI capacity-building initiatives as a key enabler of AI adoption, actual provision reveals an uneven reality. Although 83 per cent of universities overall report having implemented AI

Figure 27. Overall enabling factors for AI adoption (Percentage, n=200)



training for academic staff, suggesting that capacity development for teaching personnel has become relatively common practice, coverage drops sharply when it comes to administrative and technical staff, with only 41 per cent extending training to this group. There seems to be a distance between what institutional leaders recognize as important to enable AI adoption and what their institutions are delivering in practice across all staff groups.

Research on the factors influencing AI adoption among educators identifies institutional support (including access to training and organizational culture) as more decisive than external incentives in determining whether adoption takes place (Jin et al., 2025). The dominance of internal champions as an enabling factor aligns with Rogers' Diffusion of Innovations framework, widely applied in AI in higher education literature, which identifies innovators and early adopters within institutions as the primary transmission mechanism for new technologies (Rogers et al. as cited in Jin et al., 2025). The absence of structured training programmes and clear experimentation spaces deepens uncertainty and stagnation among faculty – a pattern that institutional leadership and support structures appear better positioned to address than individual attitudes alone (Buele and Llerena-Aguirre, 2025).

External and systemic factors including national policy regulation and incentives, cybersecurity infrastructure and financing availability are cited by fewer than 10 per cent of respondents overall. The low citation of national policy as an enabling factor suggests that university leaders do not perceive the broader policy environment as a meaningful driver of AI adoption at the institutional level; adoption is being driven from within rather than from outside. Equally striking is the near-absence of financing availability (3 per cent) as an enabling factor, suggesting that resource constraints are perceived primarily as barriers rather than facilitators – a dynamic confirmed directly in the challenges data (section 6), where lack of financial resources ranks as the single most cited obstacle to AI integration across the region, and in the budget findings (section 5.2), where 55 per cent of universities report having no specific AI budget.

5.1 Institutional strategy

The development of a formal AI policy framework has been identified as a foundational step in responsible institutional engagement with AI, providing the basis for evidence-informed decision-making about whether, how and under what conditions AI tools are deployed (UNESCO, 2025; UNESCO IESALC, 2023). Yet only 26 per cent of institutions report having a formal strategy that explicitly includes AI, while a further 32 per cent have a broader digital strategy that does not specifically address AI. The largest single group (41 per cent) has

Figure 28. Overall formal AI strategy adoption (Percentage, n=200)

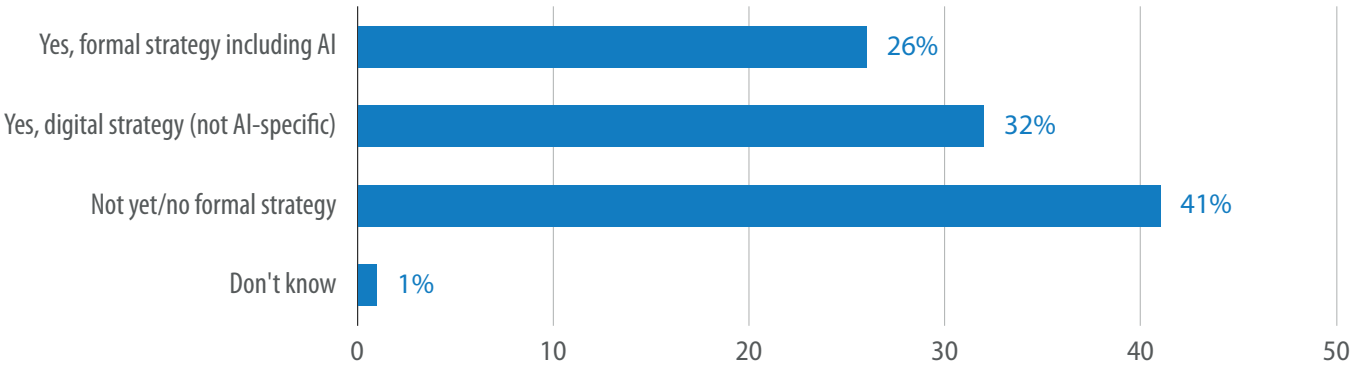
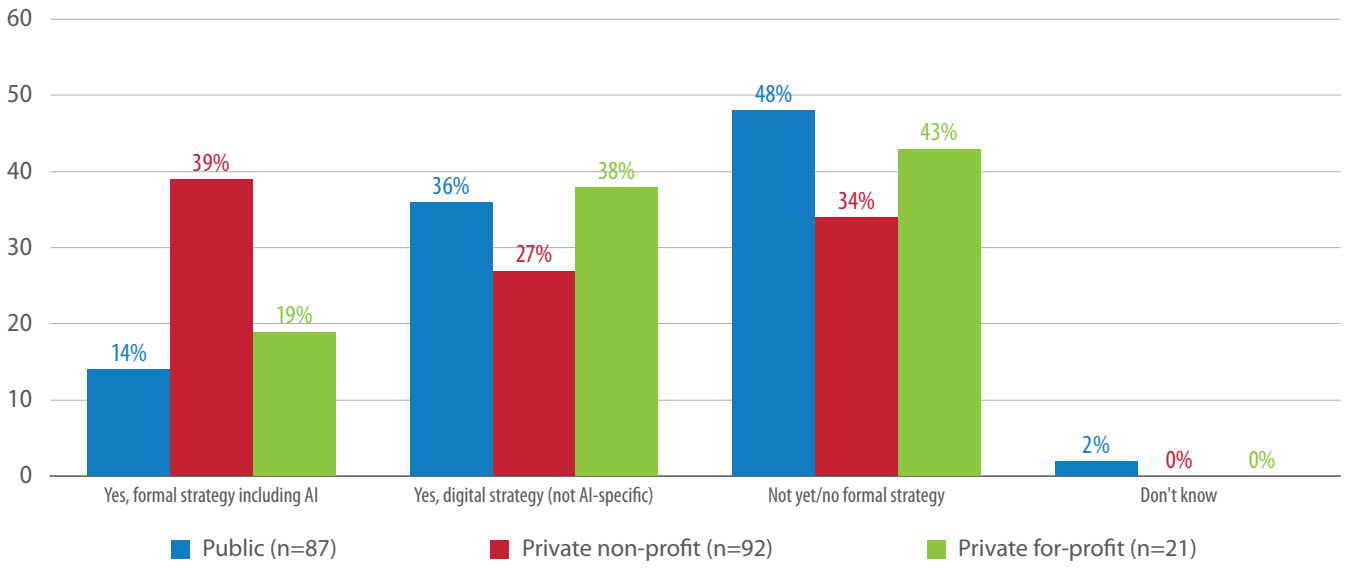


Figure 29. Formal AI strategy per institutional type (Percentage)



no formal strategy of any kind, suggesting that for an important share of universities in the region, AI integration is proceeding without an institutional framework to guide it (**Figure 28**).

This mirrors patterns in high-income countries, where nearly a third of top-tier universities across Australia, Canada, China, the United Kingdom and the United States similarly lacked any formal AI policy (Parker et al., 2025). Moreover, a UNESCO survey of higher education institutions hosting a UNESCO Chair or UNITWIN Network across 90 countries found that only 19 per cent had formal AI policies, with regional variation: around 70 per cent of institutions in Europe and North America had or were developing guidance, compared to 45 per cent in LAC (UNESCO, 2025).

The findings of the present report suggest that the institutions surveyed fall at or slightly below the regional average for LAC, reinforcing the picture of a region where AI tools are in active use but where formalized institutional frameworks to govern that use remain underdeveloped. The contrast between institution types is one of the most pronounced findings in the survey. Private non-profit universities are almost three times as likely as public universities to have a formal AI strategy (39 per cent vs. 14 per cent), a gap that could likely reflect differences in governance speed and institutional agility rather than in awareness or intent. Public universities, which must often navigate more complex approval processes and broader stakeholder accountability, appear to be catching up through broader digital strategies (36 per cent) rather than AI-specific ones. This may also reflect concerns regarding AI and its impact on education, equity and societal risks (**Figure 29**).

Technological universities present a contradiction worth noting: 63 per cent report have a digital strategy (the highest of any group); however, only 13 per cent have formalized AI specifically within it, which could suggest that digital maturity does not automatically translate into AI-specific strategic planning. Specialized universities are the most strategically underprepared with 63 per cent reporting no formal strategy of any kind (**Figure 30**).

5.2 Budget and funding

Financial investment in AI is limited across the region. Overall, only 8 per cent of the institutions surveyed report having a specific budget dedicated to AI initiatives, with private non-profit institutions leading at 11 per cent and public institutions showing the lowest rate at just 4 per cent. Resource allocation for AI implementation remains low across the region. More than half of universities (55 per cent) report no specific AI budget and only 8 per cent have a specific budget for AI initiatives. A further 30 per cent finance AI activities within a broader digital transformation or innovation budget.

The public-private divide is sharp. Public universities are the least likely to have any form of dedicated AI funding: 68 per cent report no specific budget, compared to 45 per cent of private non-profit institutions. However, public universities are by far the most reliant on national government funding (49 per cent), pointing to a structural dependency that may make their AI investment more contingent on external policy cycles than on internal institutional commitment. Private non-profit universities, by contrast, rely overwhelmingly on central institutional budgets (92 per cent), suggesting greater autonomy and financial self-determination in their AI investments (**Figure 31**).

Technological universities stand out again with 69 per cent reporting no specific AI budget despite their comparatively high levels of digital infrastructure. It should be noted that this group is small (n=16) and predominantly public (75 per cent), meaning that their budget profile may reflect the resource constraints and funding structures of public institutions as much as anything specific to their academic orientation. Specialized universities show the weakest financial position with 77 per cent reporting no specific AI budget and 13 per cent reporting no budget allocation at all) (**Figure 32**).

The resource constraint finding at the institutional level mirrors what the Latin American Artificial Intelligence Index (ILIA) 2025 documents at the national level: no country in the region exceeds the world average in AI investment relative to Gross

Figure 30. Formal AI strategy per academic orientation (Percentage)

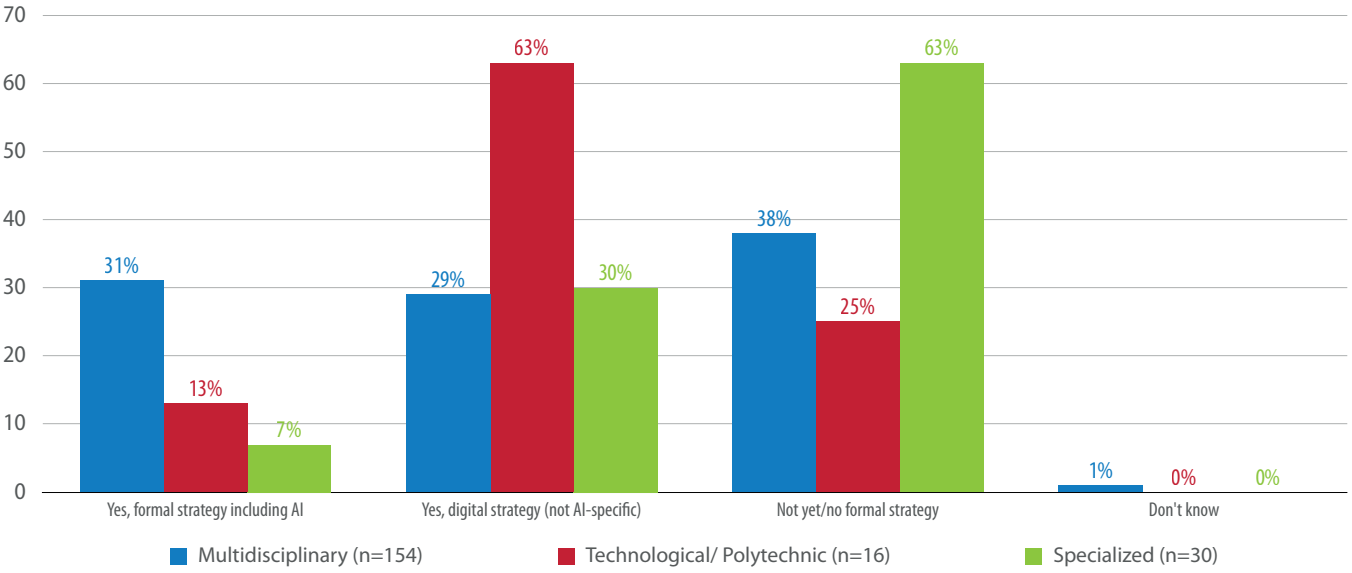


Figure 31. AI budget per institutional type (Percentage)

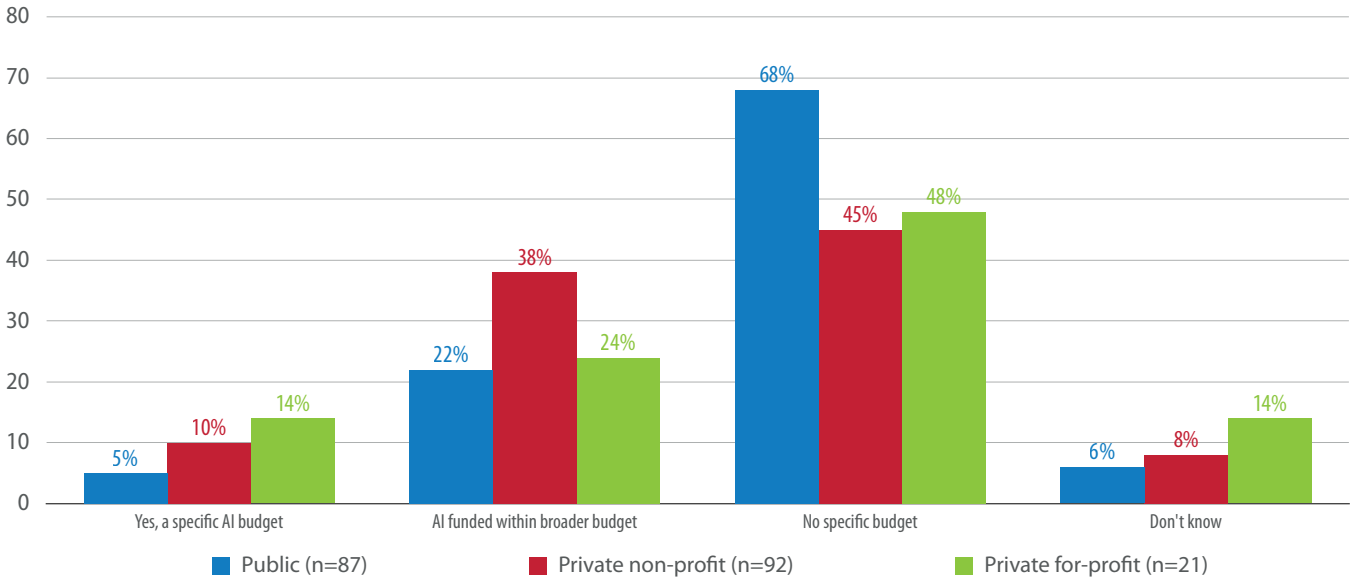
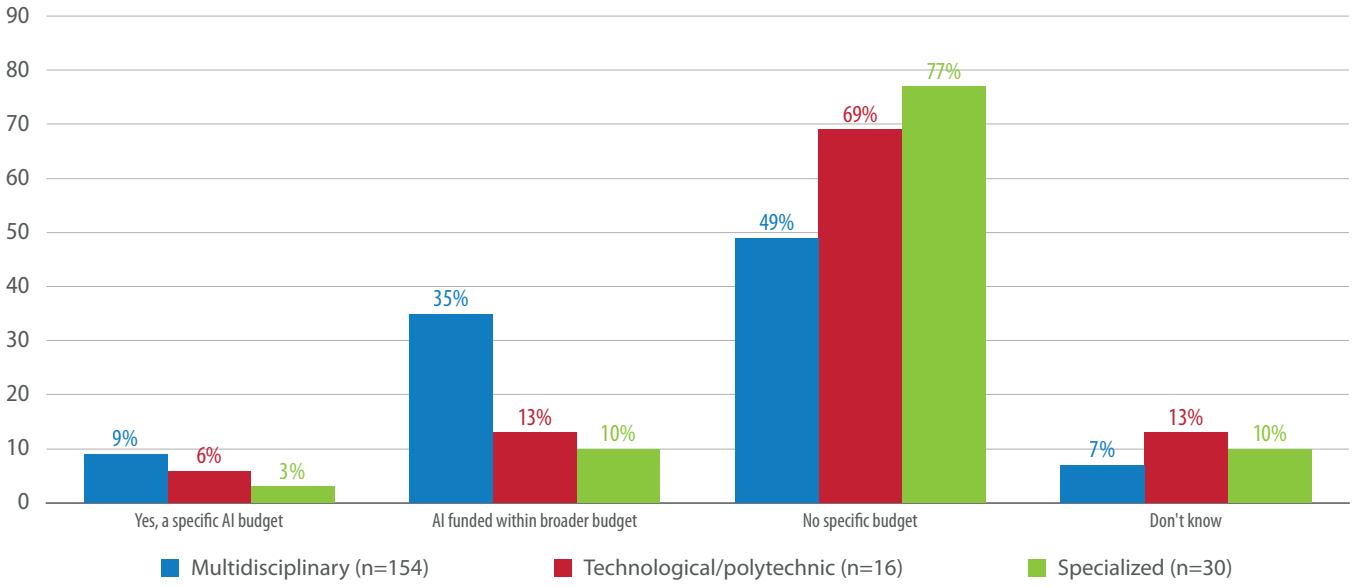


Figure 32. AI budget per academic orientation (Percentage)



Domestic Product (GDP) per capita and the regional average remains six times below that threshold (Soto et al., 2025). The pattern is consistent across scales from national governments to individual institutions; the region is characterized by high interest in AI and insufficient investment to sustain it. Financing represents a structural barrier to responsible AI integration, with institutions in the region facing particular challenges in sustaining AI investments in the absence of dedicated public funding mechanisms (Ferreyra et al., 2017; Molina and Medina, 2025; UNESCO IESALC, 2023).

5.3 AI policies and academic integrity

The policy landscape for AI in higher education across the region is still in formation. This is consistent with a broader global pattern in which the rapid integration of AI into higher education has largely outpaced the development of institutional policy and governance frameworks (Paskevicius, 2024; Pireci Sejdiu and Sejdiu, 2025). A comparative analysis of 343 top-tier universities across Australia, Canada, China, the United Kingdom and the United States found that nearly a third had no AI policy of any kind and 47 per cent

provided no guidance to students or staff on how AI could or could not be used (Parker et al., 2025). To complement these findings, the latest Digital Education Council Faculty Survey (conducted in 28 countries) found that 80 per cent of faculty do not consider their institution's AI guidelines to be comprehensive, and an equal proportion report that their institution has not clearly communicated how AI can or cannot be used in teaching, with only 5 per cent perceiving their guidelines as fully comprehensive (Digital Education Council, 2025). Taken together, these figures confirm that the governance gap documented in this survey is not a regional outlier but a widespread pattern in many regions of the world.

In the region, only 19 per cent of universities have institution-wide AI policies and a further 21 per cent have policies covering specific areas such as teaching or research. The largest single group (29 per cent) reports that policies are currently under development which may signal a positive direction but also highlights how recently this agenda has gained institutional attention. Overall, 15 per cent of institutions report no policies of any kind. These trends overall signal the need for accelerated institutional and policy-level action (**Figure 33**).

By academic orientation, policy development is most advanced among multidisciplinary universities, of which 21 per cent have institution-wide policies and a further 21 per cent have policies in specific areas (giving a combined coverage of 42 per cent).

The public-private gap persists. Private non-profit universities are more than twice as likely as public institutions to have institution-wide policies (26 per cent vs. 12 per cent). Notably, 20 per cent of public universities report that individual faculty members have developed their own informal guidelines (the highest of any group), which may reflect a bottom-up dynamic in the absence of top-down institutional frameworks. This fragmented, bottom-up pattern of policy development is documented by Azevedo et al. (2025), who find that many institutional AI guidelines are disjointed, hard to enforce and quickly outdated, leaving faculty to navigate AI use independently and without cross-departmental alignment. Jin et al. (2025), in a global study of 40 universities, similarly identify significant gaps in comprehensive policy frameworks despite widespread adoption of AI tools. Specialized universities again show the weakest policy development, with 40 per cent still in the development phase and only 10 per cent having reached institution-wide coverage (**Figure 34**).

Among the 79 universities that do have policies, *Teaching and learning* (80 per cent) and *Academic integrity* (80 per cent) are the most addressed areas, followed by *Research ethics* (72 per cent) and *Data privacy and cybersecurity* (42 per cent). These

Figure 33. Existence of AI policies (institutional) (Percentage, n=200)

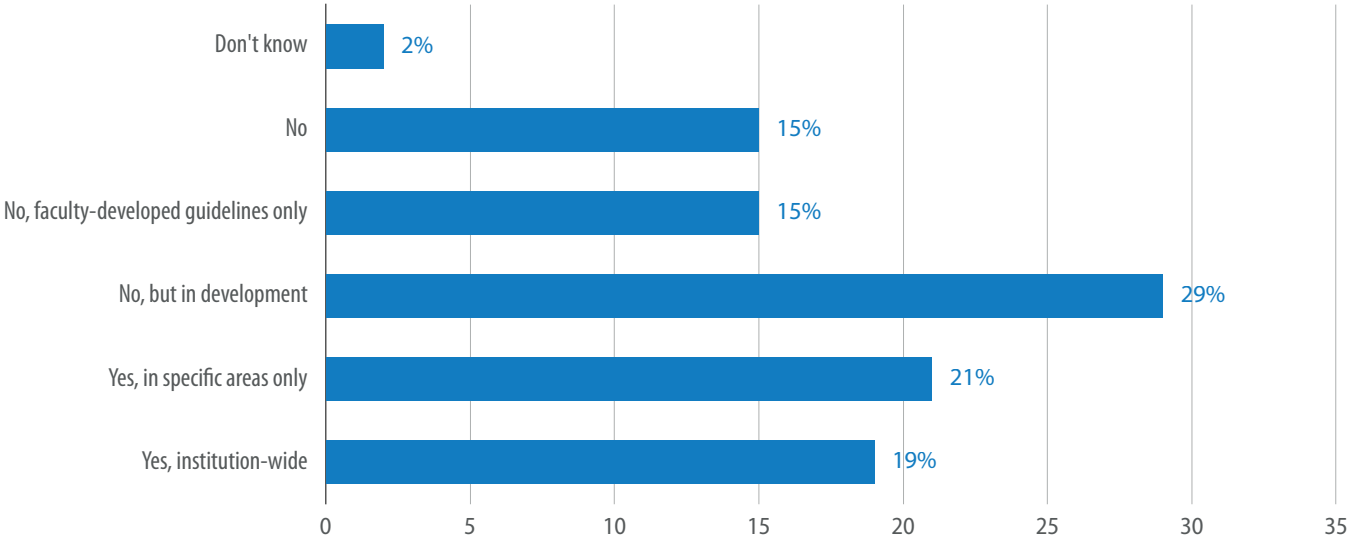


Figure 34. AI policies per institutional type (Percentage)

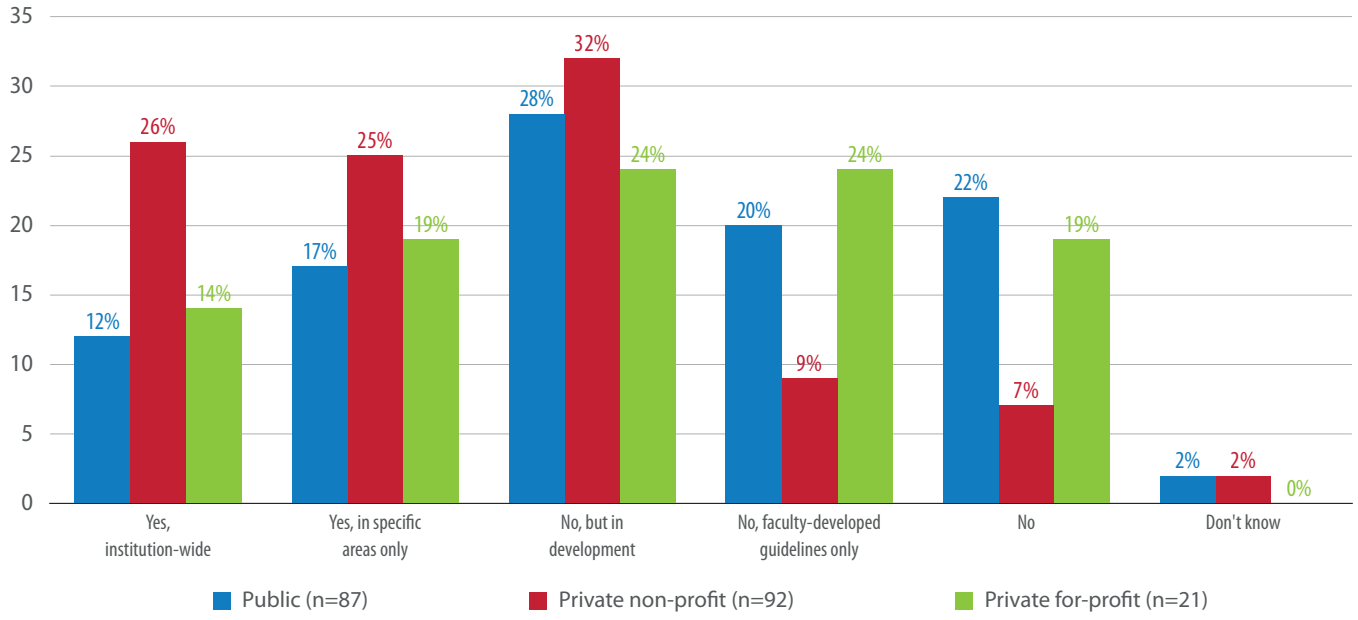
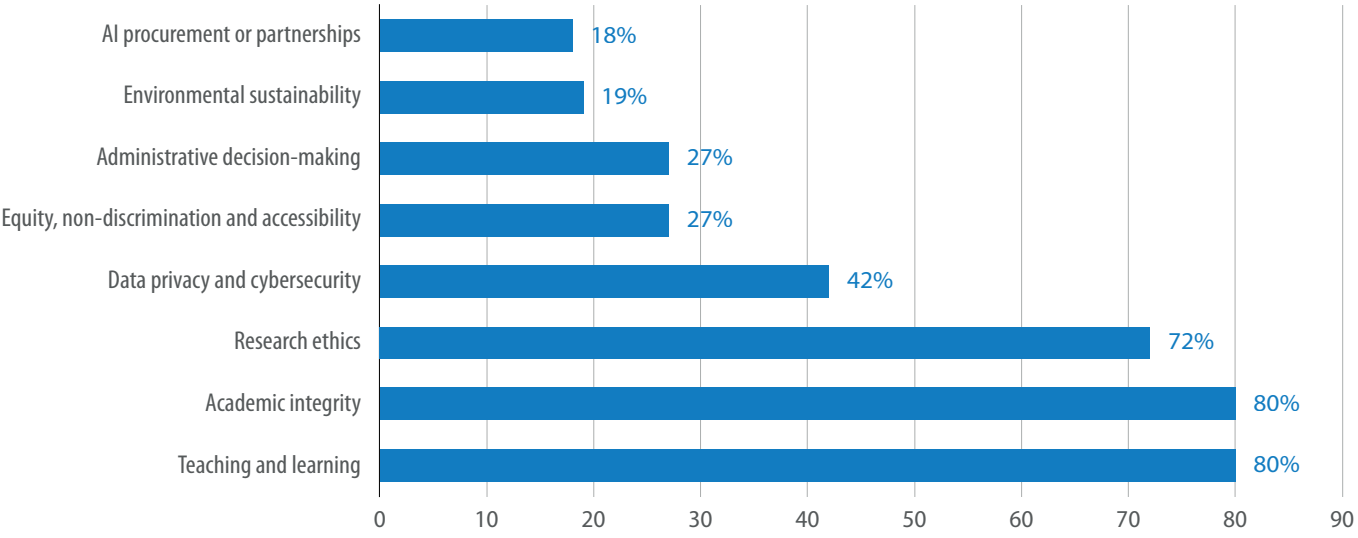


Figure 35. Areas covered by AI policies (Percentage of universities with policies, n=79)



priorities align with what the literature identifies as the most urgent policy areas. As Chan (2023) mentions, AI policy frameworks for higher education must prioritize transparency, academic integrity and human-centred pedagogy as their core pillars (Chan, 2023); data governance, equity and research ethics are also highlighted as foundational policy action areas (UNESCO, 2022).

Areas such as *Equity and non-discrimination* (27 per cent) and *Administrative decision-making* (27 per cent) are less commonly addressed, suggesting that the policy conversation has so far focused on academics rather than on broader institutional or societal dimensions of AI governance (**Figure 35**).

By academic orientation, the policy area breakdown reveals differences among the relatively small number of institutions with policies in each group (multidisciplinary n=65, polytechnic n=6, specialized n=8). *Teaching and learning* is the top priority for multidisciplinary (82 per cent) and specialized universities (88 per cent), while polytechnic institutions show a more distributed profile, with *Teaching and learning, Academic integrity, Data privacy* and *Research ethics* all cited at 50–67 per

Figure 36. Areas covered by AI policies per academic orientation (Percentage of universities with policies, n=79)

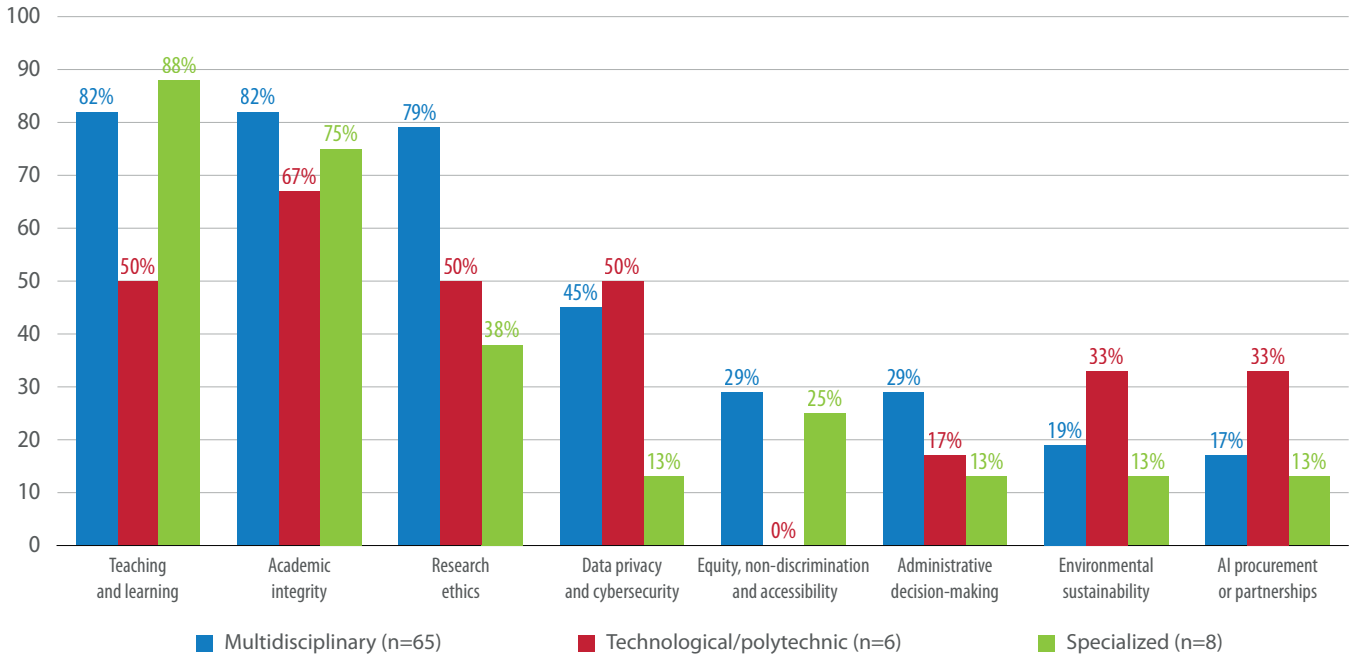
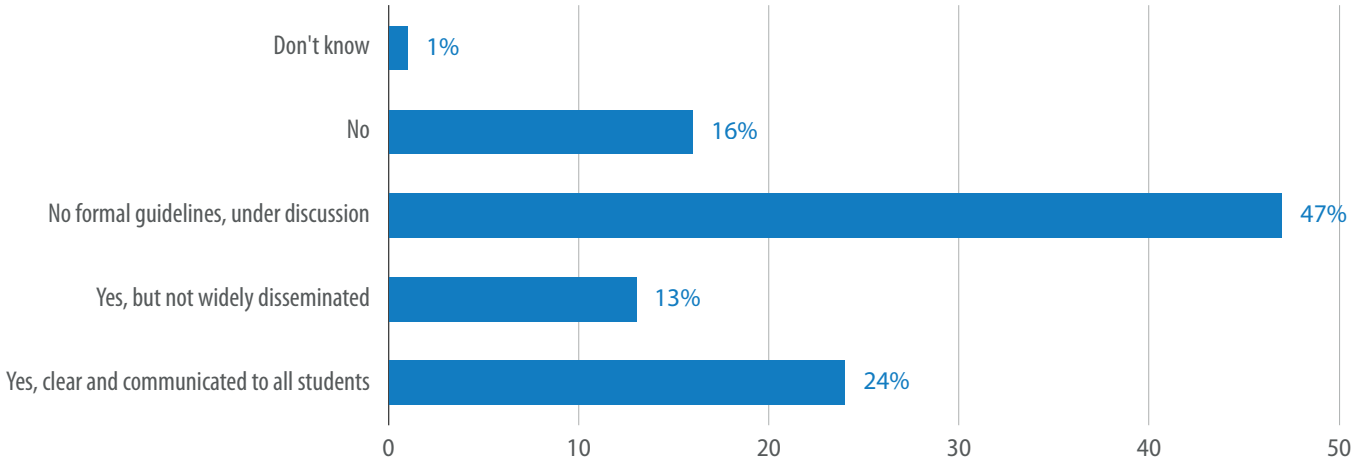


Figure 37. Overall academic integrity policies on student AI use (Percentage, n=200)



cent. The most striking difference concerns research ethics: multidisciplinary universities cover it in 79 per cent of cases, but only 38 per cent of specialized universities with policies address it (**Figure 36**).

When specifically considering academic integrity, the findings show widespread institutional unpreparedness in the face of rapid change. Overall, only 24 per cent of universities report having academic integrity guidelines on student AI use that are clear and actively communicated to the student body. A further 13 per cent have guidelines that exist but are not widely disseminated. The largest group, 47 per cent, reports that formal guidelines do not yet exist but are under discussion, while 16 per cent report no guidelines at all (**Figure 37**).

The gap between policy existence and policy communication has also been documented in a multi-methods study of AI policy in higher education, finding that even where institutions have developed AI guidelines, students frequently remain unsure whether or when they are permitted to use AI tools in their coursework, due to unclear or inconsistently communicated regulations (Yingying et al., 2025). This suggests that the problem is not only one of policy absence but of communication.

Figure 38. Academic integrity policies on student AI use per institutional type (Percentage)

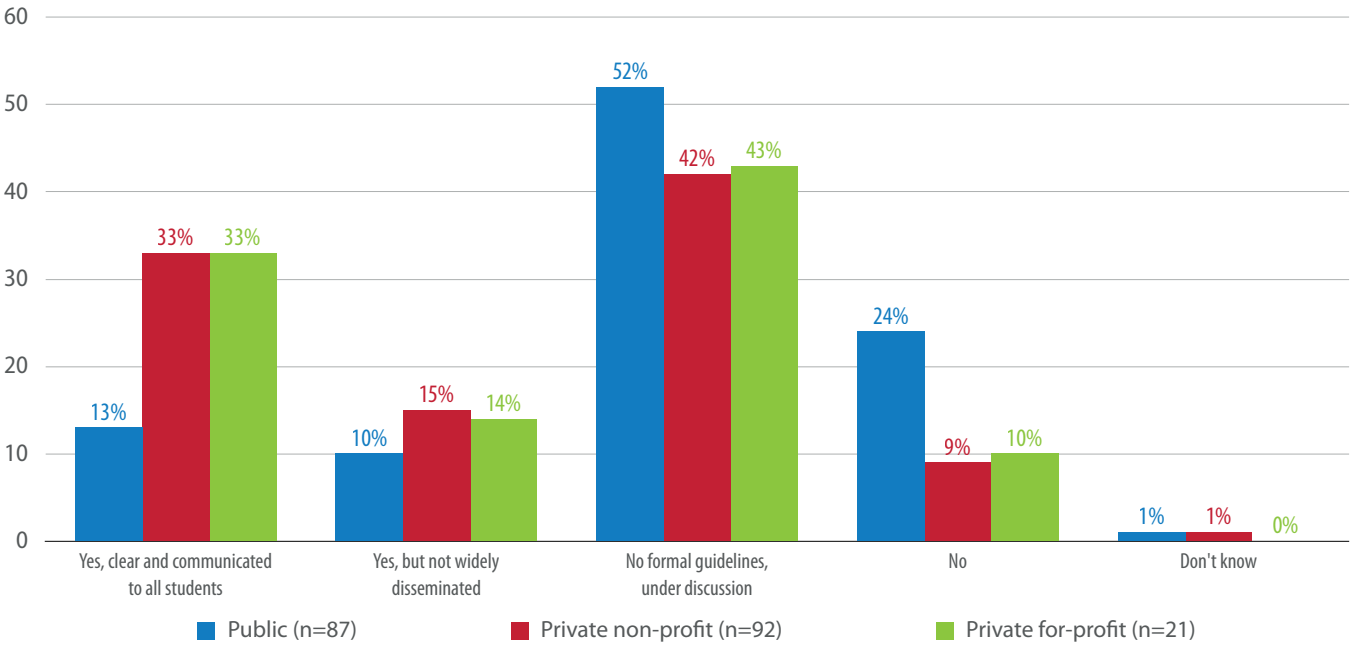
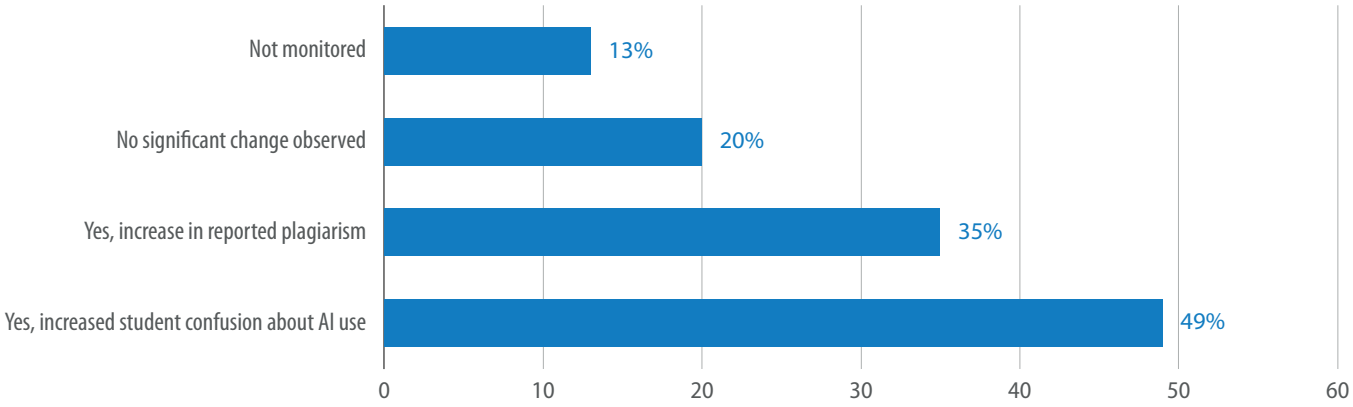


Figure 39. Overall observed changes in student misconduct (Percentage, n=200)



Considering institutional type, private non-profit universities are more than two and a half times as likely as public institutions to have clear, communicated integrity guidelines (33 per cent vs. 13 per cent). Private for-profit universities show a similarly strong result (33 per cent) (**Figure 38**).

The behavioural consequences of this policy gap are visible. Nearly half of all universities (49 per cent) report increased student confusion about what constitutes appropriate AI use, and increased plagiarism cases are reported by 35 per cent of respondents (**Figure 39**).

These findings are consistent with the broader literature on generative AI and academic integrity. In 2024, the International Center for Academic Integrity found that 58 per cent of students admitted to using AI dishonestly for assignments, highlighting the scale of the challenge (Tan and Maravilla, 2024). Also, authors argue that generative AI has transformed academic integrity from a plagiarism problem into an authorship problem, rendering traditional detection tools insufficient and requiring a fundamental rethinking of assessment design (Kofinas et al., 2024). The survey data suggest that universities in the region are encountering this challenge without the policy infrastructure necessary to respond to it systematically.

Faculty integrity concerns are equally significant. Forty (40) per cent of universities report concerns about equity and consistency in AI-assisted

Figure 40. Overall observed changes in faculty academic integrity (Percentage, n=200)

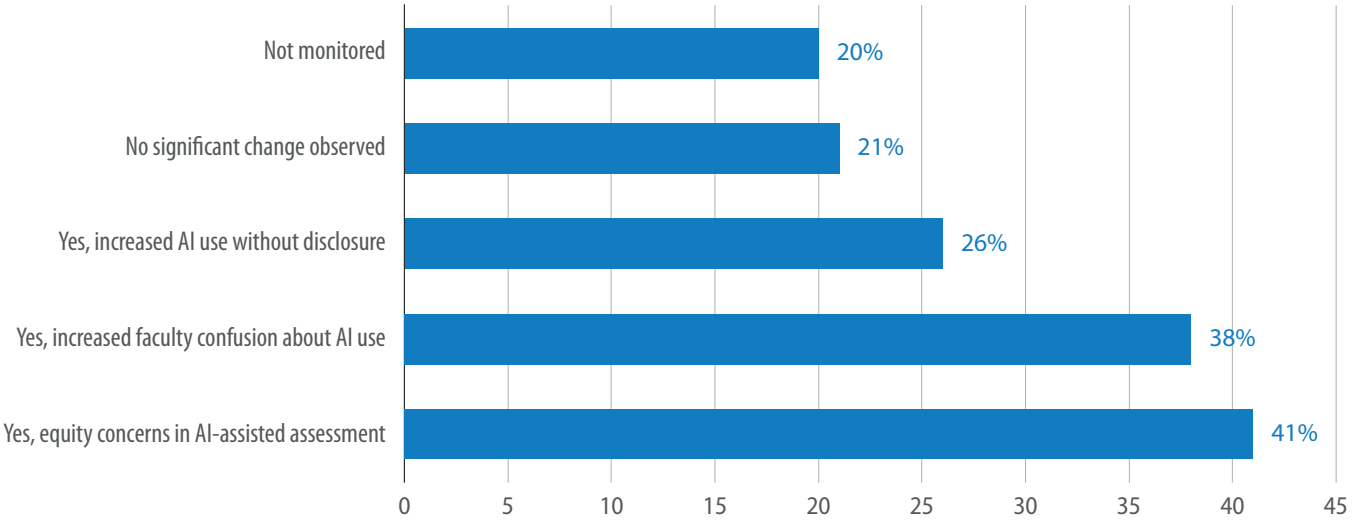
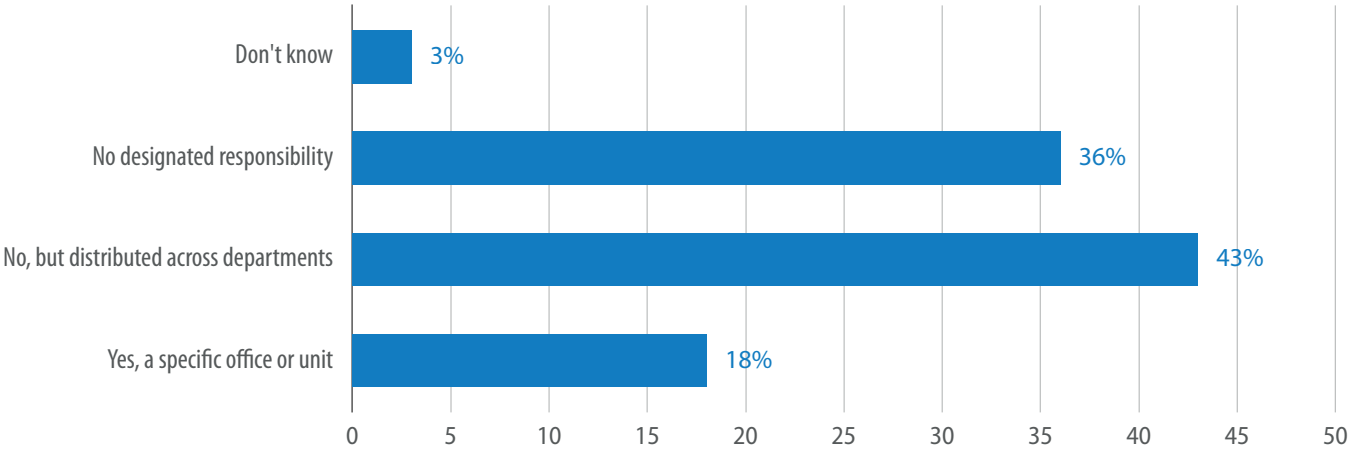


Figure 41. Overall AI governance structures (Percentage, n=200)



assessment, 38 per cent report faculty confusion about appropriate AI use and 26 per cent report increased use of AI without disclosure (**Figure 40**).

Faculty often struggle to understand appropriate AI use due to inconsistent institutional guidance. The lack of coordinated professional development and institutional support, particularly when policies differ across departments, leaves educators uncertain about implementation expectations (Azevedo et al., 2025; Chan, 2023). This survey's finding that confusion is distributed uniformly across all institution types (with no group below 30 per cent), suggests that this is a systemic rather than institutional challenge, one that requires sector-wide professional development initiatives. The high rate of non-monitoring (20 per cent) is also notable as one in five universities reports that faculty AI conduct is not being tracked.

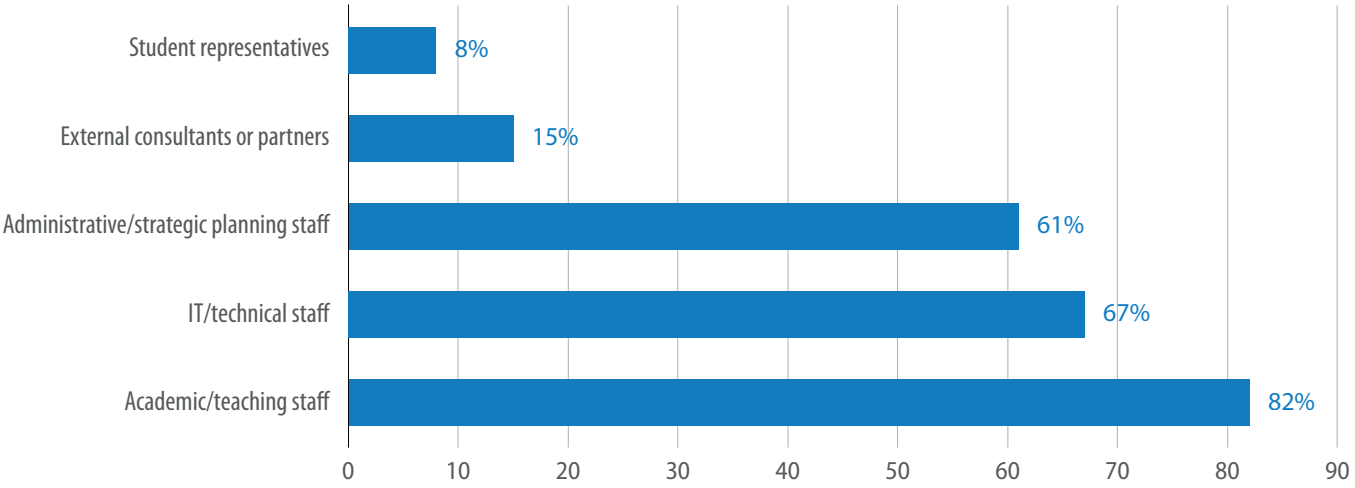
5.4 Governance structures and accountability

Formal AI governance remains the exception rather than the rule. Overall, only 18 per cent of universities report having a dedicated office or unit responsible for AI oversight, while the majority either distribute responsibilities across departments (43 per cent) or have no designated responsibility at all (36 per cent). Taken together, this means that in most universities, AI integration is being managed without a clear institutional home, which could help explain many of the policy and academic integrity gaps documented in previous sections (Azevedo et al., 2025) (**Figure 41**).

Figure 42. AI governance structures per institutional type (Percentage)



Figure 43. Overall composition of AI office or unit (Percentage, n=120)

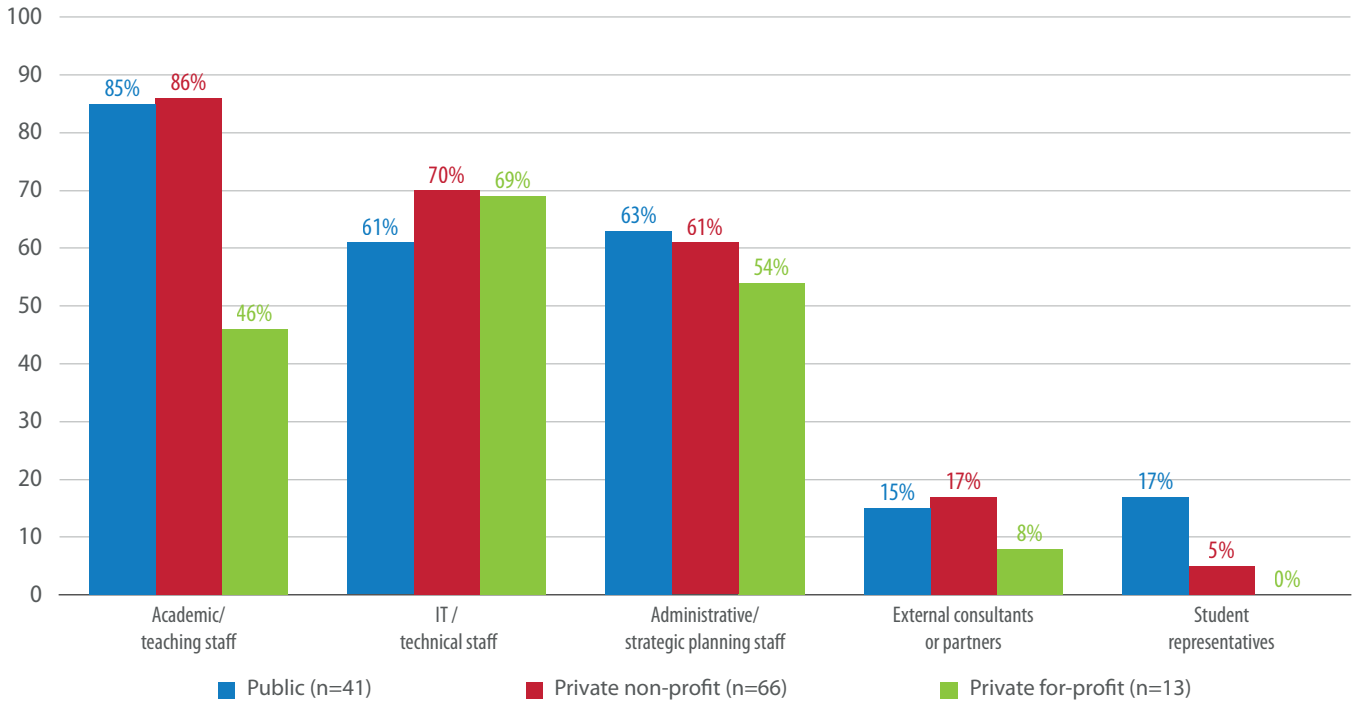


Public universities are notably weakest on this dimension: 48 per cent report no designated responsibility for AI governance, compared to 25 per cent of private non-profit universities. This mirrors the strategy findings and reinforces the pattern of slower institutional formalization in the public sector. Specialized universities also show limited governance capacity, with only 7 per cent having a dedicated office, the lowest of any group (**Figure 42**).

Among the 120 universities that reported either a dedicated office or distributed responsibilities, *Academic and teaching staff* are the most consistently represented in governance arrangements (82 per cent), followed by *IT/Technical staff* (67 per cent) and *Administrative and strategic planning staff* (61 per cent). *External consultants or partners* are included in 15 per cent of cases, reflecting a relatively limited engagement of external expertise in what remains a predominantly internal governance model. Most importantly, *Student representatives* feature in only 8 per cent of governance arrangements overall (**Figure 43**).

This already low figure masks an institutional divide: 17 per cent of public universities include student representatives compared to just 5 per cent of private non-profit institutions and no private

Figure 44. Composition of AI office or unit per institutional type (Percentage, n=120)



for-profit universities. By academic orientation, no specialized university includes student representatives in its governance structure and only one polytechnic university does so (13 per cent) (**Figure 44**).

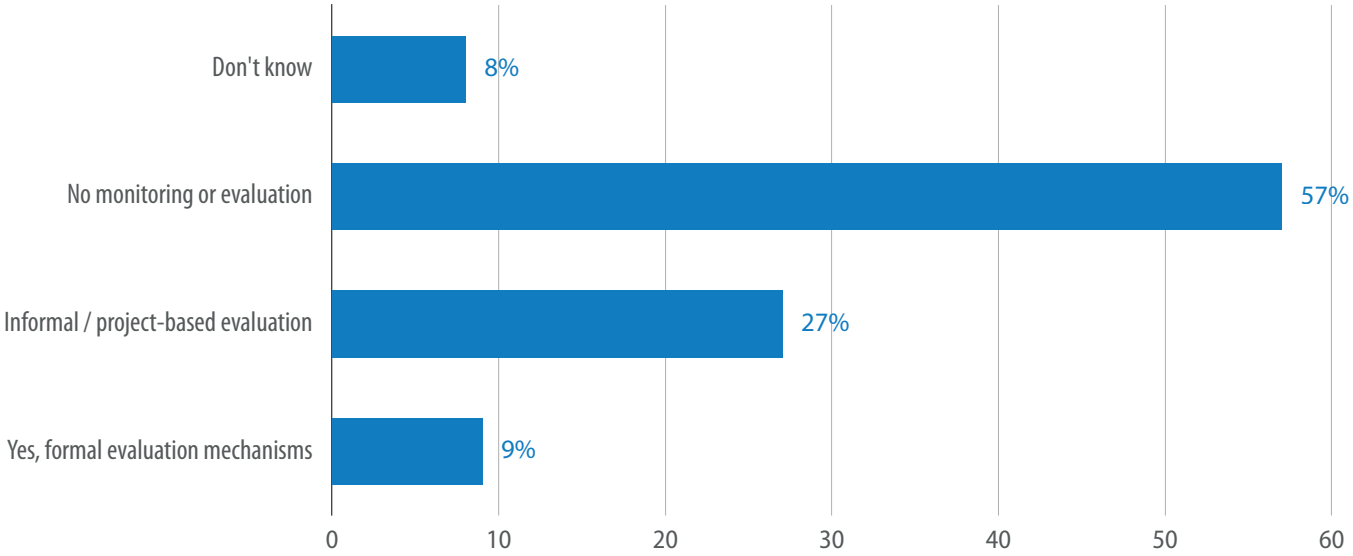
The relatively lower inclusion of administrative and strategic planning staff compared to academic and IT staff may limit the extent to which governance decisions translate into operational change, a concern echoed in the broader literature on AI governance in higher education (Khairullah et al., 2025). The low rate of student participation in AI governance structures concentrated almost entirely in the public sector raises a fundamental governance problem.

The 2021 UNESCO Recommendation on the Ethics of AI – the first global normative instrument in the field – articulates inclusive, multi-stakeholder governance of AI systems as a foundational principle, meaning that AI governance must include all stakeholder groups impacted by these technologies (UNESCO, 2022). For higher education institutions, this principle demands the inclusion of students, who are simultaneously the primary users of AI tools and the population most directly affected by AI-mediated decisions in teaching, assessment and student services. The active engagement of students alongside faculty and administrators is also stressed by the Organisation for Economic Co-operation and Development (OECD), noting that the compartmentalization of governance decisions among a narrow set of actors is an obstacle to responsible innovation (OECD, 2023). Inclusive governance models (encompassing students alongside faculty and administration) are essential for ensuring that AI policies reflect the needs and rights of all members of the academic community (Azevedo et al. 2025).

5.5 Monitoring and evaluation

The capacity to monitor and evaluate AI implementation is paramount; without it, institutions cannot determine whether AI is achieving its intended purposes, identify unintended consequences or make evidence-based decisions about where to invest, what to scale and what to discontinue. Continuous monitoring and evaluation are necessary conditions for responsible AI integration, enabling institutions to understand how AI is affecting learning processes and outcomes and to make informed adjustments over time (Chan, 2023).

Figure 45. Overall monitoring and evaluation of AI implementation (Percentage, n=200)



The survey findings reveal how underdeveloped monitoring and evaluation mechanisms remain across the region. Overall, only 9 per cent of universities report having formal evaluation mechanisms in place for AI implementation. A further 27 per cent rely on informal or project-based evaluation. The largest group, 57 per cent, report no monitoring or evaluation at all (**Figure 45**).

Situating these figures against the adoption picture presented in Section 2 makes the gap concrete. Around 87 per cent of universities report using AI in at least one area (teaching and learning, research, administration or community engagement) yet only 9 per cent have formal evaluation mechanisms in place. There are roughly 10 times more universities deploying AI than there are universities systematically measuring its outcomes. Even among the most active adopters, using AI across three or more functional areas simultaneously, 37 per cent report no monitoring of any kind.

Among the 147 universities using AI in teaching and learning – the area of highest adoption and most direct student impact – 49 per cent have no monitoring in place. It could be argued that the region is scaling AI implementation faster than it is building the infrastructure to understand what that implementation is doing.

By institution type, the monitoring gap is most pronounced among public universities, of which 62 per cent report no monitoring at all, the highest rate of any institution type and more than 10 percentage points above private non-profit universities (52 per cent). This is consistent with the broader pattern documented throughout the report, in which public universities consistently show weaker governance development across strategy, policy, budget, and now, evaluation. Private non-profit universities show the highest rate of informal or project-based evaluation (32 per cent), suggesting that even where formal mechanisms are absent, there is somewhat more activity-level reflection occurring in this sector (**Figure 46**).

By academic orientation, specialized universities show the highest rate of *No monitoring* (60 per cent), followed by polytechnic (56 per cent) and multidisciplinary institutions (56 per cent). The differences across academic orientations are relatively small; this is a general gap rather than one concentrated in a particular type of institution. What is interesting is that formal evaluation is marginal across all groups: just 9 per cent of multidisciplinary, 6 per cent of polytechnic and 10 per cent of specialized universities report having formal mechanisms in place (**Figure 47**).

The absence of monitoring infrastructure has consequences that extend beyond institutional efficiency. Universities that do not systematically evaluate their AI implementation cannot

Figure 46. Monitoring and evaluation of AI implementation per institutional type (Percentage)

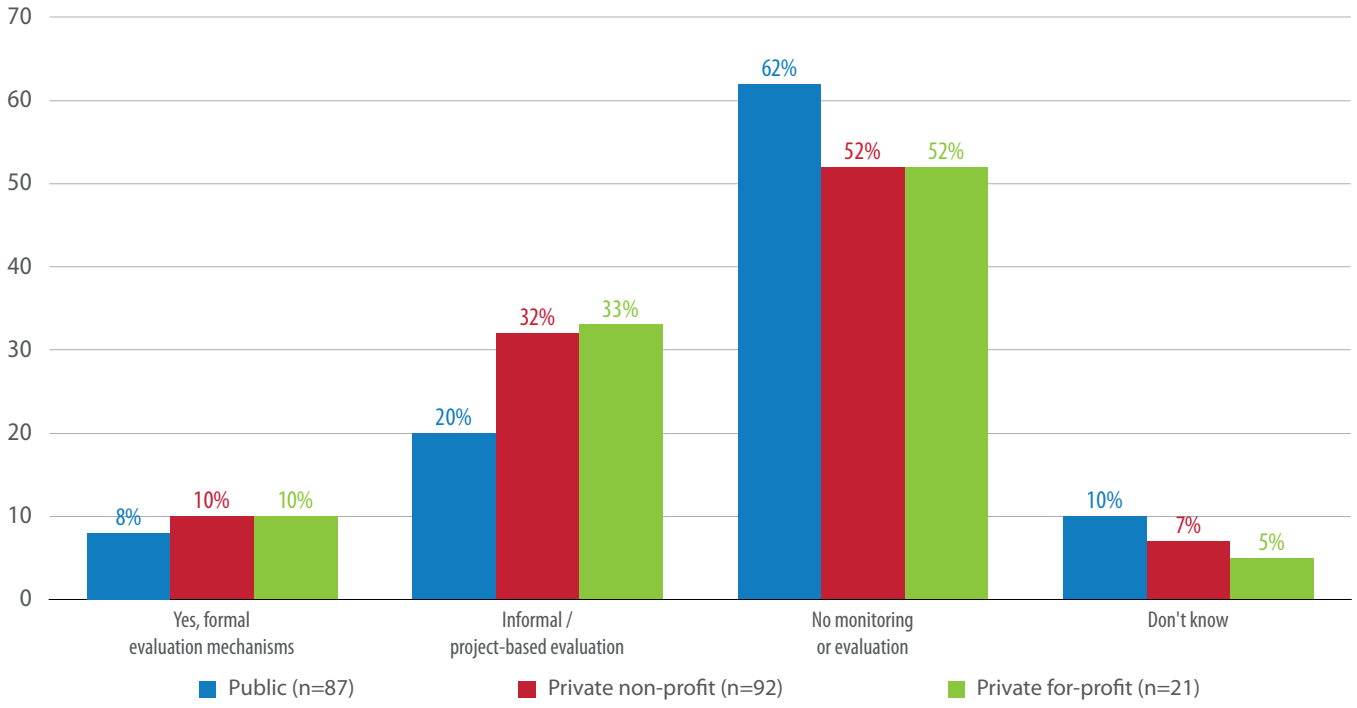
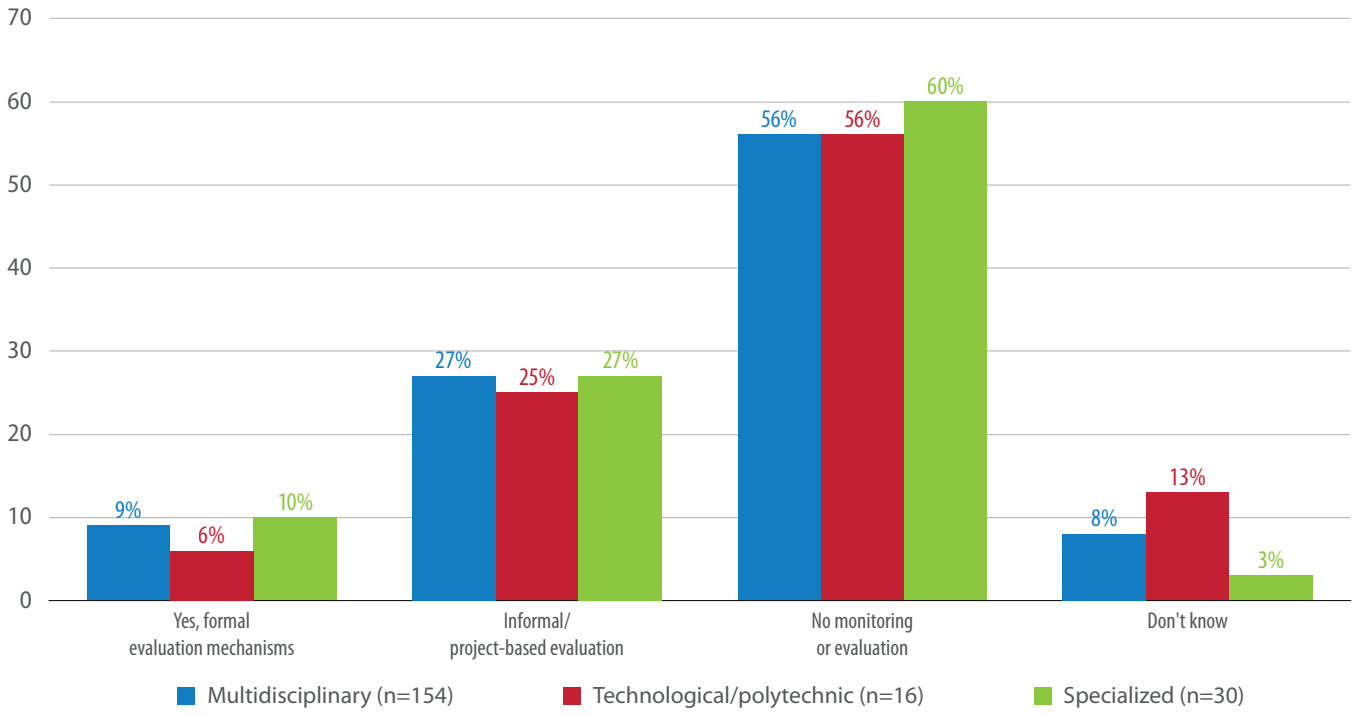


Figure 47. Monitoring and evaluation of AI implementation per academic orientation (Percentage)



demonstrate accountability to students, staff or external stakeholders, cannot identify whether AI tools are exacerbating or reducing equity gaps, and cannot contribute to the regional evidence base needed to inform policy.

6. Challenges to AI integration

Institutional representatives were asked to rank eight potential challenges from 1 (most important) to 8 (least important). The framing of this question assumes a degree of engagement with AI adoption; institutions that have deliberately chosen to limit or avoid AI integration are therefore less likely to be reflected in these responses. The results are demonstrated in Table 4.

Lack of financial resources emerged as the top-ranked challenge by a wide margin, at 3.26 points. Financial constraints emerge consistently across global and regional evidence as a significant structural barrier to AI adoption, particularly pronounced in the Global South where investment gaps, infrastructure deficits and limited public funding mechanisms compound one another (Soto et al., 2025; UNESCO IESALC, 2023) (**Table 4**).

Table 4. Ranking challenges

Challenge	Overall (n=200)
Lack of financial resources	3.26
Insufficient staff expertise	3.62
Limited technical infrastructure	4.01
Ethical or governance concerns	4.07
Resistance to change	4.54
Lack of policy guidelines	4.71
Data privacy or cybersecurity risks	5.78
Uncertainty about long-term impact	6.01

Insufficient staff expertise, already discussed in this report, and *Limited technical infrastructure* are cited as the next top challenges. The infrastructure challenge reflects a broader structural issue that extends across regions. As noted in recent literature, the digital divide remains a substantial obstacle, with equitable access to the infrastructure required for AI often unevenly distributed across institutions and regions, a challenge that is particularly acute in resource-limited contexts (Molina and Medina, 2025).

Ethical or governance concerns, Resistance to change and the *Lack of policy guidelines* also feature as prominent concerns. Notably, the lack of clear policy guidelines ranks sixth overall (average rank 4.71), despite the significant policy gap documented in earlier sections of this report. This apparent paradox (universities recognizing the policy gap but not ranking it as a top constraint) is significant. It may suggest that institutions are proceeding with AI adoption regardless of the policy environment. The broader literature documents a pattern in which institutional AI adoption consistently outpaces governance frameworks, with universities adapting practice before policy catches up (Jin et al., 2025; Pireci Sejdiu and Sejdiu, 2025; UNESCO IESALC, 2023), a dynamic that mirrors the historical trajectory of previous technology waves in higher education. Data privacy or cybersecurity risks and uncertainty about long-term impact appear as the least pressing concerns

By institution type, financial resources rank as the dominant challenge across all groups, with some differences. Public universities show the highest concentration of this concern: 44 per cent rank it as their single most important challenge, compared to 32 per cent of private non-profit institutions and 38 per cent of private for-profit institutions. Technical infrastructure weighs more heavily on public universities, with 20 per cent ranking it first compared to 11 per cent of private non-profit and 10 per cent of private for-profit institutions. This pattern is consistent with the resource and infrastructure gaps documented throughout this report. Private for-profit universities present a different profile: *Insufficient staff expertise* is ranked first by 24 per cent of these institutions, the highest rate of any institution type and nearly double the overall average of 13 per cent, which is coherent with the finding in section 4 that for-profit institutions show the weakest staff AI training provision overall (**Figure 48**).

One finding requires particular attention. No public university ranked data privacy and cybersecurity as its most important challenge, despite public institutions typically managing the largest volumes of sensitive student and research data in the sample.

Figure 48. Challenges by institution type (Percentage)

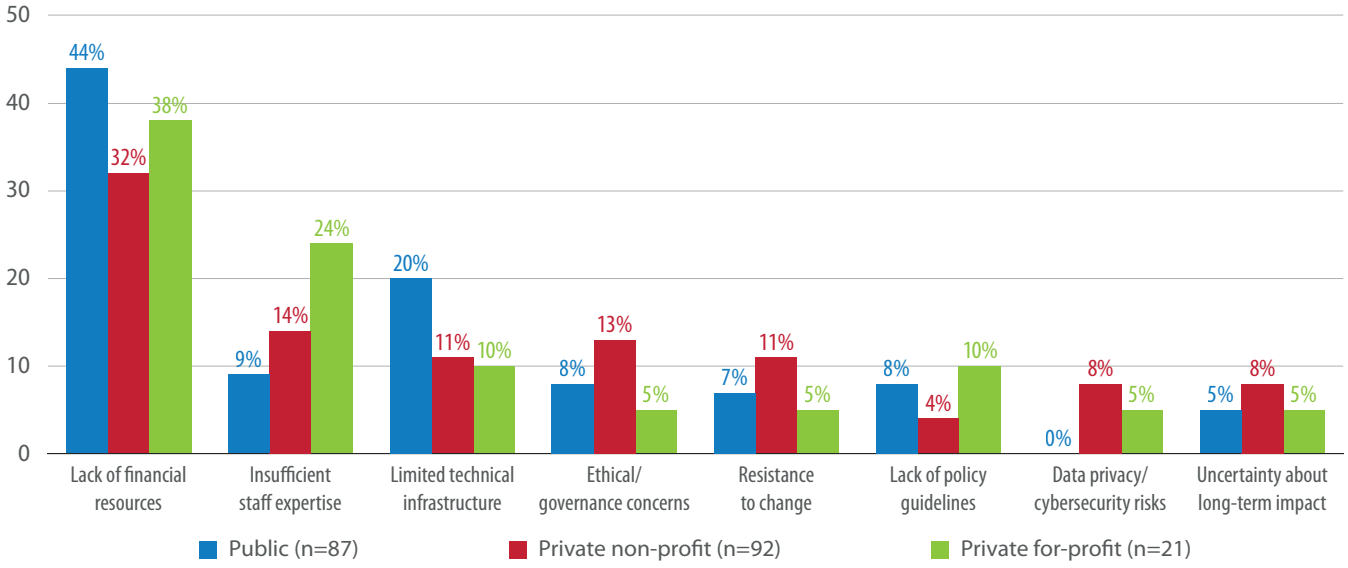
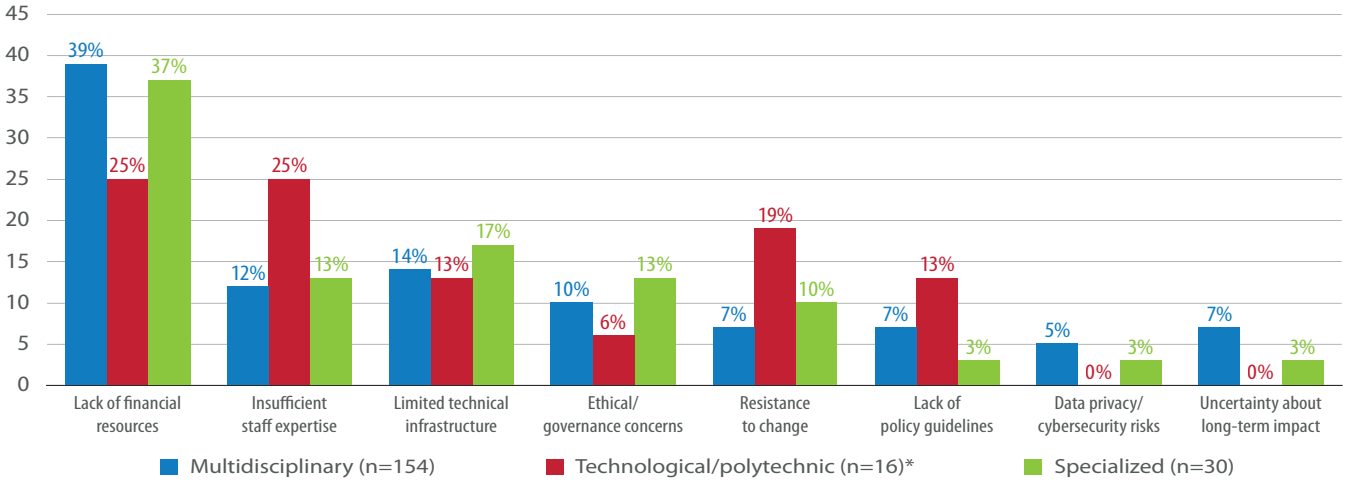


Figure 49. Challenges by academic orientation (Percentage)



Whether this reflects genuine confidence in existing systems, lower awareness or a different framing of institutional risk, is not clear from the survey data alone but it sits in some tension with the data privacy concerns expressed elsewhere in the sector.

By academic orientation, specialized universities show the lowest average rank for financial resources (2.87), confirming that resource constraints are felt most acutely in this group, consistent with their predominantly small size and limited budget capacity documented in section 5.2. Polytechnic universities present two interesting findings. First, *Insufficient staff expertise* is ranked first by 25 per cent of these institutions (the highest rate of any academic orientation group and nearly double the overall average), which may appear counterintuitive given their generally stronger technological profile. It could reflect a distinction between technical AI competency and the pedagogical and governance expertise needed to deploy AI responsibly in educational contexts. Second, *Resistance to change* is cited as the single most important challenge by 19 per cent of polytechnic universities, compared to just 7 per cent of multidisciplinary institutions. In these predominantly public, technically oriented institutions, cultural and organizational barriers to change appear more pronounced than their academic orientation might suggest, a reminder that governance is as much a cultural challenge as a technical one. Given the small size of this group (n=16), both findings should be interpreted with caution (**Figure 49**).

7. Conclusions and recommendations

The survey reveals that AI adoption in higher education institutions in the LAC region is a complex, multidimensional phenomenon, affecting different functional areas in distinct ways. Teaching and learning leads adoption, followed by research, administration and community engagement, each with varying degrees of uptake, visibility and impact. Equally important are the management and governance conditions within institutions – strategies, policies, budgets and oversight mechanisms – that shape how AI is implemented, monitored and supported. Together, these dimensions highlight not only where AI is being used, but also the gaps in leadership awareness, institutional frameworks and enabling resources.

The conclusions are organized in two complementary layers: dimension-specific findings that examine patterns within each dimension, and cross-cutting findings that identify structural patterns that recur across dimensions.

7.1 Dimension-specific findings

The following paragraphs examine each dimension in detail and provide key insights to understanding these patterns, revealing both the opportunities AI presents and the structural challenges universities must address to integrate it responsibly and effectively.

AI adoption in teaching and learning: widespread use with uneven foundation. Teaching and learning is the dominant site of AI adoption with 74 per cent of universities reporting current use. Among universities using AI in teaching, nearly 9 in 10 rely on general purpose tools such as ChatGPT, Copilot or Gemini, a rate that is uniform across institution types and academic orientations. This uniformity may reflect a bottom-up dynamic: AI entering the classroom through tools that students and faculty were already using and not through institutional planning. Private non-profit universities lead adoption at 84 per cent against 68 per cent for public institutions but the more consequential divide lies in the conditions under which AI use is taking place, including the training provided, the policies in place and the monitoring mechanisms available.

AI in research: strong uptake with limited institutional awareness. AI adoption in research stands at 57 per cent, the second highest of any core area, but the analytically significant finding is the visibility gap as 23 per cent of senior institutional leaders responded that they did not know whether AI was being used in research at their own institution. In a survey directed at senior institutional and academic leaders at rector, dean and strategic planning levels, this could imply a management and governance gap. It could indicate that AI in research is diffusing at the level of individual researchers and groups, without the strategic guidance of leadership. The applications driving adoption are practical – accelerating data processing and analysis, improving research quality and streamlining literature reviews – and consistent with global evidence on how generative AI is transforming research (Molina and Medina, 2025). Again, the concern is with the absence of institutional oversight over how AI is being used, given that research using AI carries distinct ethical implications around data integrity, authorship and reproducibility that institutional frameworks need to address.

AI in administration: limited adoption with significant visibility gaps. AI adoption in administration is reported by just over a third of surveyed universities (34 per cent), but the defining characteristic of this domain is the 'don't know' rate of 29 per cent, a figure that rises to 38 per cent among public universities. When more than one in four senior leaders cannot confirm whether AI is being used in their own institution's administrative operations, it could point to a model in which operational AI is being deployed outside the visibility and accountability of central leadership. The governance concern is that AI tools applied in student-facing contexts carry significant implications around data use and algorithmic accountability that are difficult to manage responsibly when leadership visibility of these deployments remains low.

AI in community engagement: a distinct pattern of AI adoption. Community engagement records both the lowest adoption rate (20 per cent) and the highest 'don't know' rate (32 per cent) of any dimension, which could reflect its position as the most distant from daily academic work and least visible to institutional leadership. However, it is worth considering whether lower AI adoption in this domain is necessarily a gap to be addressed. Community engagement is fundamentally relational, built on trust, local knowledge and context-specific interaction with communities. The case for deep AI integration in this mission is less obvious than in other dimensions, and the appropriate role of AI here warrants careful deliberation rather than an assumption that higher adoption rates would constitute progress. What the data does signal is that institutional leadership has limited visibility into how AI, if used, is being deployed in community-facing activities.

AI governance in universities: driven by individuals and constrained by institutional capacities. The management and governance findings are the most consequential in the survey as they define the conditions under which all the adoption documented above is taking place. While 87 per cent of universities report using AI in at least one dimension (teaching and learning, research, community engagement and administration), only 26 per cent have a formal institutional strategy that explicitly addresses AI, 19 per cent have institution-wide policies, 8 per cent have a dedicated AI budget, 18 per cent have a designated governance structure, and just 9 per cent have formal mechanisms to monitor and evaluate their AI implementation. More than half (57 per cent) report no monitoring of any kind, meaning the region has roughly 10 times more universities deploying AI than universities systematically measuring what that deployment is doing. The enabling factors identified by university leaders complete this picture: internal working groups and individual champions lead at 71 per cent, while structural enablers (digital infrastructure, external partnerships and national policy incentives) are cited by fewer than 10 per cent of respondents. It could be said that AI adoption in the region is being driven by motivated individuals operating within institutions that have not yet built the frameworks to govern what those individuals are achieving. Training provision reflects the same asymmetry: 83 per cent of universities train academic staff, but only 41 per cent extend training to administrative and technical staff, and 35 per cent offer no student-facing AI training at all. Among universities already using AI in teaching and learning, 25 per cent do not provide their students with any training, leaving students to navigate an AI-saturated environment without institutional guidance, a situation the consequences of which are already visible: 49 per cent of universities report increased student confusion about appropriate AI use and 35 per cent report increased plagiarism cases.

7.2 Cross-cutting findings

Beyond the dimension-specific findings examined in section 7.1, six structural patterns emerge across all areas of AI adoption and governance. These patterns should be read in the historical context established in Section 5: the governance gaps documented here reflect a structurally familiar dynamic in which technology adoption in higher education consistently precedes the institutional frameworks designed to govern it (Isaifan, 2026; Jin et al., 2025; Palvia et al., 2018). However, the speed and complexity of AI adoption (and the distinctive risks it introduces) make an accelerated governance response more necessary now than in previous technology transitions (Isaifan, 2026).

1. Adoption hierarchy

Access, not institutional strategy, shapes which domains adopt AI first. Teaching and learning leads adoption at 74 per cent, followed by research (57 per cent), administration (34 per cent) and community engagement (20 per cent). This tracks how close each dimension is to the tools students and faculty use daily, particularly generative AI, reported by 90 per cent of universities that have adopted AI in teaching and learning. The hierarchy is not the result of deliberate institutional prioritization but of the differential accessibility

of AI tools across dimensions. Community engagement, the mission most distant from daily academic work, is also the one most invisible to senior leadership with a 'don't know' rate of 32 per cent, the highest in the survey.

2. Institutional type

The public-private divide is the most consistent and consequential structural gap in the survey. Private non-profit universities report higher rates than public institutions on each dimension measured. The gap is most pronounced in formal strategy (39 per cent vs. 14 per cent), staff AI training (92 per cent vs. 75 per cent) and student curriculum integration (42 per cent of private non-profit universities vs. a 40 per cent share of public universities reporting no student training at all). This systematic gap suggests that public universities face structural barriers to AI governance that compound across all dimensions. These finding also stress structural capacity. Public universities carry the largest student populations and the broadest social mandates, and the students they serve are mostly from lower-income backgrounds with the greatest need for the potential benefits of AI. A persistent and widening AI readiness gap between public and private institutions therefore carries equity implications that extend well beyond higher education itself (Wong et al., 2025).

3. Academic specialization

Specialized universities face the most acute and consistent governance deficits across every dimension. Across every governance dimension in the survey – formal strategy (63 per cent with no strategy), dedicated budget (77 per cent with no specific AI budget), institution-wide policies (only 10 per cent) – specialized universities come out weakest. This is particularly concerning because these are institutions that train students for specific professional fields (health sciences, teacher education, law, business) where the ethical and practical implications of AI for future professional practice are immediate and concrete. The governance deficit in specialized universities could present a potential systemic risk for the professional sectors their graduates will go on to work in.

4. Enablement model

The mismatch between what drives adoption and what sustains it is a structural vulnerability. University leaders point to internal working groups and champions (71 per cent), staff training initiatives (66 per cent) and committed management (52 per cent) as the main enablers of AI adoption at their institutions. National policy incentives and external financing feature in fewer than 10 per cent of responses. This people-driven adoption dynamic helps explain both the pace of change and its fragility. Rogers' Diffusion of Innovations framework identifies individual champions as the primary transmission mechanism for new technologies within organizations, but also recognizes that adoption driven by champions alone, without reaching the stage of institutional routinization, remains vulnerable to disruption when those individuals move on or lose support. When the enabling conditions rest on people, progress depends heavily on whether the right individuals happen to be in the right place at a given institution. This people-driven dynamic is itself historically familiar. Research on the adoption of technology in education identifies early adopters as the primary initial transmission mechanism, with institutional routinization following only later and unevenly (Jin et al., 2025). The distinctive challenge with AI is that the risks associated with ungoverned use for student data, academic integrity and equitable access are significant enough that waiting for routinization to occur organically is unlikely to be adequate.

5. Student protection

Students are the primary users of AI yet the least protected actors in the current institutional landscape. They are the primary users of AI tools with 86 per cent already using them in their studies globally (Digital Education Council, 2024). Yet, according to the survey, they are simultaneously the group least likely to receive formal training, least represented in governance structures and most directly affected by the academic integrity consequences of inadequate institutional guidance. Nearly half of all universities (49 per cent) report increased student confusion about what constitutes appropriate AI use, and 35 per cent report a

rise in plagiarism cases. Yet only 24 per cent of institutions have clear, actively communicated academic integrity guidelines on student AI use. Students appear in governance structures in only 8 per cent of institutions overall and not at all in private for-profit or specialized universities. This governance gap carries rights-based dimensions that go beyond institutional management. As the 2021 UNESCO Recommendation on the Ethics of AI makes clear, inclusive multi-stakeholder governance is not optional but foundational to responsible AI integration (UNESCO, 2021).

6. Accountability

The monitoring deficit makes responsible AI integration and evidence-based policy-making extremely difficult. With 57 per cent of universities reporting no monitoring or evaluation of AI implementation whatsoever, and only 9 per cent having formal mechanisms in place, the sector finds itself scaling AI without any systematic way of measuring what that scaling is doing. This is not simply a management problem. It means universities cannot demonstrate to students, staff or external stakeholders whether AI is achieving its intended purposes, cannot identify whether AI tools are widening or narrowing equity gaps, and cannot contribute to the regional evidence base that policy-makers need to make informed decisions.

7.3 Recommendations

The following recommendations are organized across two levels: institutional and national policy. They are grounded directly in the survey findings and are intended to be concrete and actionable.

7.3.1 For higher education institutions

Develop a formal AI strategy that integrates governance from the outset. The survey finds that 41 per cent of universities have no formal institutional strategy of any kind relating to AI, and only 26 per cent have a strategy that explicitly addresses it. A strategy developed without an integrated governance dimension (covering policy, ethics and accountability, budget and monitoring) is unlikely to close the adoption-governance gap that this survey documents. Institutions should develop or update their AI strategies to include, at minimum: (i) a designated governance structure with clear responsibilities, (ii) a policy framework covering teaching, research, academic integrity and data privacy, (iii) a realistic budget line for AI activities, (iv) a capacity-building plan and (v) a monitoring plan with defined indicators.

Institutions that lack a strategy could begin with a structured internal diagnostic, mapping current AI use across dimensions; identifying existing governance gaps; and consulting academic staff, administrative staff and students before drafting a new strategy. Institutions that already have a strategy could audit it against the dimensions listed above and publish the results internally as a basis for accountability.

Among institutions in the region that have moved in this direction, Tecnológico de Monterrey (Mexico) offers a publicly documented reference point. The university has published a five-pillar AI strategy covering teaching and learning, ethical use, research and development, talent development and operational improvement, alongside separate downloadable guidelines for the ethical use of AI addressed specifically to students and to faculty (Tecnológico de Monterrey, n.d.). Institutions seeking a structured framework to guide policy development could also consult the *EDUCAUSE 2024 Action Plan: AI Policies and Guidelines*, which provides a practical template covering governance, operations and acceptable use that institutions can adapt to their own context (Jenay and McCormak, 2024).

Establish a dedicated AI governance structure with student representation. Only 18 per cent of universities have a dedicated office or unit responsible for AI oversight, and 36 per cent have no designated governance responsibility at all. Among the universities that do have some form of governance arrangement, student representatives are included in only 8 per cent of cases. Institutions should establish a designated governance body with a defined mandate, clear accountability lines and formal student representation.

In practical terms, this does not necessarily require the creation of a new institutional unit. Where resources are limited, a cross-functional AI committee (drawing on existing roles in academic affairs, IT, legal or compliance, and student services) can fulfil this function provided it has a formal mandate, meets on a regular basis and reports to senior leadership. Student representation should be structural and not advisory: it is important that student members have full participation rights and a defined role in internal policy review processes. As good practice, institutions should publish the membership of their governance body and make decisions and minutes accessible to the broader university community.

An example from outside the region comes from the University of California, Los Angeles (UCLA) in the United States, which established a formal Advisory Committee on AI in Teaching and Learning in 2025. The committee is explicitly constituted to include students, faculty and staff, and its mandate covers governance, AI literacy, accessibility, instructor training and institutional infrastructure. The committee reports directly to the Vice Provost for Teaching and Learning and is co-chaired by the university's Chief Data and AI Officer and the Director of its Teaching and Learning Centre, ensuring that AI governance does not default to IT departments alone (Eskilson, 2025). While the institutional context differs from that of universities in LAC, the model demonstrates that student representation in AI governance structures can be formalized and operationalized within existing university governance arrangements without the creation of new institutional units.

Close the student training gap and make AI literacy a graduation-level competency. Among universities already using AI in teaching and learning, 25 per cent offer no student-facing AI training of any kind. A further 41 per cent of all surveyed universities offer only an elective course model, meaning AI literacy is an optional addition rather than an embedded institutional expectation. Universities should move from elective provision toward integrating AI literacy as a transversal competency across programmes and disciplines. This does not require every institution to develop a standalone AI curriculum; it requires academic planning to embed the critical and practical dimensions of AI use (including its risks, ethical implications and limits) into existing teaching across fields. The 49 per cent rate of reported student confusion about appropriate AI use, and the 35 per cent rate of increased plagiarism cases, are measurable consequences of the current training gap and should provide institutional leaders with a concrete basis for action.

A practical starting point is a curriculum mapping exercise in which academic departments identify existing courses where AI literacy dimensions (critical evaluation of AI outputs, ethical use, disciplinary-specific applications and awareness of limitations) can be integrated without requiring new standalone modules. Institutions could designate a lead academic unit responsible for coordinating this process and for developing shared learning resources that departments can adapt. Progress toward embedding AI literacy could be tracked as part of existing curriculum review cycles, with defined milestones and reported outcomes.

Two universities in the region illustrate what this can look like in practice. In Mexico, Tecnológico de Monterrey has launched a programme called Develop AI Savvy with the aim of ensuring that students graduate with AI competencies embedded across disciplines and is redesigning over 44 degree programmes to integrate AI by 2026. Its 2024 *Report on Educational Innovation* documents that 43 per cent of professional-level students already took at least one subject with AI support during that year (Ruiz, 2025). In Chile, the Pontifical Catholic University of Chile launched its ConectIA initiative in May 2024, targeting comprehensive AI integration across the university by 2026, and established AcademIA, a dedicated platform to build AI literacy and digital capabilities across its staff and student community (Barrera and Azeez, 2024). Both institutions are private, and the governance and resource conditions they operate under differ significantly from those of most public universities

in the region. They nonetheless demonstrate that embedding AI literacy as an institution-wide expectation, rather than an elective add-on, is achievable within the LAC context and does not need to be built from the ground up.

Extend AI training to administrative and technical staff. While 83 per cent of universities provide some form of AI training to academic staff, only 41 per cent extend training to administrative and technical staff. This gap is significant given that AI adoption in administrative functions is already occurring. Administrative staff who encounter AI tools in their daily work without training to understand their limitations, ethical implications and governance requirements, could be a source of risk. Institutions should audit the AI tools currently in use across administrative functions and ensure that staff in those functions have access to appropriate training, including on data privacy and acceptable use.

Institutions could begin by conducting an internal audit of AI tools currently in use across administrative functions, mapping which tools are deployed, by whom, for what purposes and under what (if any) institutional authorization. This audit could then inform a targeted training plan, differentiated by role and function: a staff member using AI to draft a document has different training needs from one using it for student data processing or financial reporting. Training content should cover, at minimum, the capabilities and limitations of the tools in use, data privacy obligations, acceptable use boundaries and escalation procedures when AI outputs are uncertain or potentially harmful. Institutions should also consider designating an AI liaison within each major administrative unit, not necessarily a technical expert, but someone with sufficient familiarity to support colleagues and flag emerging issues to the central governance body.

A system-level example of how this kind of training can be organized comes from the United States, where the University of California (UC) launched a four-part AI Essentials webinar series in spring 2025 through its UC AI Council, explicitly designed to support faculty, staff and administrators across all UC campuses in responsibly adopting and managing AI tools. The series addressed practical governance questions (including pre-adoption risk assessment, cross-functional procurement oversight and long-term accountability mechanisms) and was made available to all staff regardless of their technical background (University of California, 2025). While the scale of the UC system is exceptional, the underlying model, a centrally coordinated training programme differentiated by role and function and made available across multiple institutions, is replicable at the level of a national higher education system or a consortium of universities, which could be a practical pathway for smaller institutions in LAC that lack the resources to develop such programmes independently.

Ensure an M&E framework for AI implementation as an integral part of AI strategy. Only 9 per cent of universities report having formal evaluation mechanisms for their AI implementation, while 57 per cent report no monitoring of any kind. An institution cannot manage what it does not measure, and in the absence of monitoring, it is not possible to determine whether AI tools are achieving their intended purposes, exacerbating or reducing equity gaps, or whether unintended consequences are emerging at scale. Institutions should establish, at a minimum, a baseline monitoring framework that tracks AI use across functional areas, collects structured feedback from students and staff, and periodically reviews outcomes against stated objectives. This does not require expensive infrastructure; it requires institutional intent and a clear assignment of responsibility. Monitoring data should feed directly into the strategy and governance structures creating a feedback loop between deployment decisions and evidence of impact.

As a starting point, institutions could define a minimum set of indicators covering four dimensions: adoption (which AI tools are in use, across which missions and functions, and at what scale), preparedness (what proportion of staff and students have received training, and of what kind), outcomes (whether stated objectives for AI use are being met based on structured feedback from users) and risk

(whether issues related to academic integrity, data privacy or equitable access have emerged and how they have been addressed). These indicators do not require sophisticated data infrastructure; many can be tracked through existing administrative systems, annual staff and student surveys, and regular reporting from the governance body. Institutions should set a defined review cycle, at minimum annual, and ensure findings are reported to senior leadership and made available to the university community.

An example of how monitoring requirements can be built into quality assurance at a national level comes from Australia where the Tertiary Education Quality and Standards Agency (TEQSA) issued a formal request to all registered higher education providers in June 2024 requiring each institution to submit a credible action plan to address the risks that generative AI poses to integrity. The initiative achieved a 100 per cent response rate and TEQSA subsequently published a sector-wide toolkit based on the plans received, identifying emerging good practice across three dimensions: process, people and practice (TEQSA, 2024). While the institutional context differs from that of universities in LAC, the model demonstrates that national quality assurance bodies can play a catalytic role in requiring and supporting systematic monitoring of AI integration across an entire higher education system.

Address the academic integrity gap through assessment redesign. The survey documents that 49 per cent of universities report increased student confusion about appropriate AI use and 35 per cent report increased plagiarism cases. The deeper problem, however, seems to be that clearer policies alone do not solve this issue. Generative AI has transformed academic integrity from a plagiarism problem into an authorship problem (Kofinas et al., 2024), making traditional detection approaches insufficient and requiring a fundamental rethink of how student learning is assessed. Policies that prohibit or restrict AI use but leave unchanged the essay formats, take-home assignments and standardized tests that AI can most easily complete, are unlikely to reduce misconduct. The more durable intervention is assessment redesign. Institutions should invest in faculty development that supports the creation of tasks requiring demonstrated reasoning, situated knowledge or in-person performance, which are more resistant to AI substitution and more meaningful as measures of learning. Where AI use is permitted within an assessment, the design should make the student's own thinking visible and evaluable. Communicating policies clearly remains necessary, but it is not sufficient and it should follow from assessment design rather than substitute for it.

Concretely, institutions could establish or designate an academic development unit or assign this function to an existing teaching and learning centre with a specific aim to support assessment redesign in the context of AI. This unit could offer structured workshops for academic staff on designing AI-resistant and AI-transparent assessment tasks, develop and share a bank of assessment models adapted to different disciplines and course formats, and provide individual consultations for departments undergoing curriculum review. Where no such unit exists, institutions should identify a small working group of faculty with relevant expertise and mandate them to develop internal guidance within a defined timeframe. Progress on assessment redesign should be incorporated into the monitoring framework with institutions tracking the proportion of programmes that have reviewed their assessment practices considering AI and reporting on outcomes.

The same Australian national quality assurance process offers a relevant reference for assessment redesign. TEQSA has published dedicated guidance on assessment reform for the age of AI, explicitly moving away from detection-based approaches and toward structural redesign of assessment tasks that require demonstrated student reasoning and cannot be easily substituted by AI-generated outputs (TEQSA, 2023). The guidance is accompanied by a growing repository of institutional case studies from Australian universities documenting how different types of institutions have approached this challenge in ways that reflect their own contexts. While

originating in Australia, the pedagogical principles underpinning the guidance are now tied to specific disciplines and could be applicable to the LAC context.

7.3.2 For national policy-makers

Develop or update national AI strategies to include explicit, actionable provisions for higher education. National ministries responsible for both AI and higher education should work to develop coordinated strategies that set clear expectations for institutional AI governance, provide reference frameworks for policy development, and connect higher education AI integration to broader national priorities in innovation, equity and workforce preparation. The Santiago and Montevideo ministerial declarations provide a regional normative foundation; the next step is translating that foundation into national instruments that give universities something concrete to align with. The *National AI Strategy 2024–2030* of Uruguay offers a relevant regional reference point as it combines a governance framework with defined institutional structures and oversight mechanisms, a capacity-building pillar with targeted training programmes, and monitoring provisions with periodic review cycles (AGESIC, 2024). The *UNESCO Guidance for Generative AI in Education and Research* provides a complementary normative framework that countries can draw on to develop higher education-specific provisions without starting from zero (UNESCO, 2023).

In practical terms, national strategies should include, at minimum, three higher education-specific components: (i) a governance expectations framework that specifies what institutional AI policies, oversight structures and accountability mechanisms are required or recommended, (ii) a capacity development roadmap that sets national targets for staff and student AI literacy and identifies the funding instruments through which those targets will be pursued and (iii) a data and monitoring commitment that defines what information institutions are expected to report, at what frequency and to which national body. Ministries should establish an interministerial working group (bringing together education, science and technology, and digital economy portfolios) with a defined mandate and timeline to develop these components. Where national strategies already exist but do not address higher education specifically, a dedicated higher education annex or implementation plan should be developed in consultation with university leaders, student representatives and civil society.

Establish dedicated public funding mechanisms for AI governance capacity in universities. The survey documents that 55 per cent of universities have no specific AI budget and that public universities have the lowest rate of dedicated AI funding at just 4 per cent. The ILIA 2025 Index confirms that no country in the region exceeds the world average in AI investment relative to GDP per capita, with the regional average six times below that threshold (Soto et al., 2025). Financial constraints are the most cited barrier to AI integration, ranked as the single most important obstacle by 38 per cent of university leaders. Policy-makers should establish targeted public funding mechanisms for AI governance capacity, not simply AI adoption. Rather than an investment to simply procure AI tools, this is an investment in the institutional capacity to deploy those tools responsibly.

Public universities could be the primary beneficiaries of such funding, given that the survey consistently documents the most acute governance gaps, the lowest policy development rates and the most limited budgetary capacity in this sector. Funding should be explicitly directed at governance capacity, covering the development of institutional AI policies, oversight structures, staff training programmes and monitoring frameworks, rather than at tool procurement, which risks deepening adoption without strengthening the institutional conditions for responsible use. Ministries of education could work with national higher education funding bodies to identify existing budget instruments through which this kind of targeted allocation could be channelled, whether through competitive project funding, baseline institutional grants or regional

shared services arrangements that allow smaller institutions to access governance expertise and model policy frameworks they could not develop independently.

Promising models for how this kind of investment can be structured already exist internationally. The Responsible AI UK (RAI UK) programme of the United Kingdom, a £31 million strategic government investment channelled through the national research funding body UK Research and Innovation (UKRI), offers a precedent. It funds universities and research organizations specifically to develop responsible AI skills, governance frameworks and policy tools, explicitly distinguishing this category of investment from AI tool procurement and framing governance capacity as a prerequisite for responsible deployment (Responsible AI UK, 2024). At the institutional level, the Center for Artificial Intelligence (C4AI) at the University of São Paulo in Brazil illustrates a different but complementary model: a tripartite co-financing arrangement among the Fundação de Amparo à Pesquisa do Estado de São Paulo (São Paulo Research Foundation), a private technology company (IBM) and the university itself, which together fund an AI research centre embedded within a public university whose mandate includes research on the societal impact of AI and AI public policy (Allison, 2020). While C4AI is primarily a research centre rather than a governance capacity initiative, it demonstrates that structured co-financing between public and private actors can sustain institutionally embedded, policy-oriented AI work in public universities without requiring governments to bear the full financial burden alone.

Develop national guidance for AI academic integrity standards that institutions can adopt and adapt. The survey documents that 47 per cent of universities report that their academic integrity guidelines are under discussion but not yet formalized and a further 16 per cent have no guidelines at all. In the absence of national reference frameworks, individual universities are developing these policies from scratch, producing the fragmented landscape that the literature consistently documents. National ministries of education, working with higher education quality agencies and accreditation bodies, should develop national guidance frameworks for AI academic integrity that establish minimum standards while allowing institutional adaptation. This is not a call for uniform national policy; the diversity of the higher education sector means that one-size-fits-all approaches are rarely effective. It is a call for the provision of a shared reference point that reduces the burden on individual institutions and ensures a minimum floor across the sector.

In practical terms, the development of such frameworks could follow a structured consultative process involving, at minimum, three actor groups: (i) academic staff and faculty associations, who understand the disciplinary diversity of assessment practices, (ii) student representatives, who are the most directly affected by integrity policies and among the least consulted in current governance arrangements and (iii) higher education quality assurance agencies, which are best positioned to ensure that the resulting frameworks are aligned with existing accreditation standards and can be embedded in institutional review cycles. The framework itself should address, at minimum, four dimensions: (i) definitions of permissible and impermissible AI use across different assessment contexts, (ii) disclosure and transparency requirements for both students and staff using AI in academic work, (iii) institutional responsibilities for communicating policies clearly and consistently and (iv) review mechanisms that allow frameworks to be updated as AI capabilities evolve. The *UNESCO Guidance for Generative AI in Education and Research* provides a normative foundation that national frameworks can draw on and adapt to regional and institutional contexts, reducing the need for each country to develop its approach from first principles (UNESCO, 2023).

The quality assurance and accreditation mechanisms outlined in the following recommendation provide the natural vehicle through which these national frameworks can be embedded and enforced at the institutional level.

Integrate AI literacy and governance requirements into national higher education quality assurance and accreditation frameworks. Students across the region are already using AI at very high rates. The gap between student AI use and institutional preparation could be considered a quality issue. National accreditation bodies and quality assurance agencies are well-positioned to address it by establishing minimum standards for AI literacy curriculum integration as a condition of institutional recognition. Similarly, accreditation frameworks should begin to incorporate governance standards (for AI policy, data privacy and student protection) as part of institutional quality assessments. Embedding these requirements in existing quality assurance cycles is a direct and proportionate policy lever that does not require the creation of a new regulatory infrastructure.

National quality assurance agencies could consider a phased approach to integration. In a first phase, agencies should incorporate AI governance as a thematic area within existing institutional self-assessment instruments, requiring universities to report on whether they have an AI policy, what training provisions are in place for staff and students, and how academic integrity in the context of AI is being addressed. This phase does not require new standards; it requires adding structured questions to existing review processes and using the resulting data to build a national evidence base on institutional preparedness. In a second phase, drawing on that evidence base, agencies should develop minimum threshold standards for AI literacy integration and governance, subject to broad consultation with institutions, student bodies and faculty associations before adoption. This sequenced approach reduces the risk of imposing requirements that are disconnected from institutional realities and ensures that accreditation serves as a lever for improvement rather than a compliance burden. Regional coordination through existing bodies such as the Ibero-American Network for Quality Assurance in Higher Education could support the harmonization of approaches across countries and reduce duplication of effort.

Invest in regional data infrastructure and a shared evidence base on AI outcomes in higher education. The monitoring gap documented in this survey (57 per cent of universities report no monitoring of any kind for their AI implementation) means that the region lacks the institutional data needed to make evidence-based policy decisions about AI in higher education. Individual institutions that are not monitoring their own AI outcomes cannot contribute to a shared evidence base, and policy-makers who lack that evidence base cannot design effective interventions. Governments across the region, working through existing regional and global platforms, such as UNESCO IESALC and the UNU Global AI Network, should invest in building a shared regional evidence infrastructure: common indicators, standardized data collection and periodic regional reviews of AI adoption, governance and outcomes in higher education.

Building a shared regional evidence infrastructure requires action at three connected levels. At the institutional level, the monitoring framework provides the foundation: institutions that track a minimum set of indicators on AI adoption, preparedness, outcomes and risk generate the data that, when aggregated, constitute a regional evidence base. This connection between institutional monitoring and regional data infrastructure is not automatic as it requires that national and regional bodies define common indicators in advance, so that data collected independently by institutions is comparable across contexts. At the regional level, UNESCO IESALC is well-positioned to coordinate the development of a common indicator framework, drawing on the survey instrument used in this report as a starting point and refining it through consultation with national ministries, quality assurance agencies and higher education institutions across the region. At the global level, the UNU Global AI Network facilitates synergies in the expertise of academia, the innovation of the private sector, the foresight of policy-makers and the engagement of civil society, which can be tapped by national authorities and universities in sharing knowledge of such indicators and developing research tools for monitoring them.

7.3.3 For regional and international organizations

Support the development of a shared regional evidence base on AI in higher education. The survey documented a near-total absence of systematic monitoring within universities across the region, meaning that the evidence base available to policy-makers for informed decision-making on AI in higher education is extremely thin. Regional organizations could coordinate a periodic, comparative data collection effort on AI adoption, governance and training provision in higher education across LAC countries, building on the methodology developed in this survey. A regional monitoring framework of this kind would allow countries to track progress over time, identify where governance gaps are widening or narrowing and benchmark institutional performance against regional averages in a way that no individual country can do alone.

Provide targeted technical assistance to support AI governance capacity-building in public universities. The survey documents that public universities face the most acute governance deficits. Regional and international organizations could establish or expand dedicated technical assistance programmes directed specifically at public universities, offering support in the form of model policy frameworks, governance toolkits, staff training resources and peer-learning mechanisms that allow institutions with limited capacity to access expertise they cannot develop independently. The *UNESCO Guidance for Generative AI in Education and Research* could provide a normative foundation for such programmes to draw on and adapt to the regional context (UNESCO, 2023).

Mobilize development finance specifically for AI governance capacity in higher education. The recommendation to national governments to establish dedicated public funding mechanisms for AI governance capacity will be difficult to implement in a region where no country exceeds the world average in AI investment relative to GDP per capita, and where the regional average is six times below that threshold (Soto et al., 2025). Development partners could play a catalytic role by making AI governance capacity in higher education an explicit and eligible category within existing education and digital development financing instruments. This is an investment in the institutional conditions for responsible deployment, and it addresses a market failure that neither universities nor national governments in the region are currently able to correct on their own.

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Annex

Annex I – Priority areas for AI leadership development

The five priority areas presented below derive from the findings of this survey. Based on evidence from the region captured in this report, they present what university leaders most urgently need to understand in order to adopt AI ethically and responsibly.

1. AI strategy and governance for university leaders

Leaders need to understand how to translate institutional values and mission into a coherent AI strategy; how to design governance structures with clear mandates, defined accountability lines and meaningful stakeholder participation; how to distinguish between administrative AI decisions and governance questions; and how to build institutional routines that sustain AI governance beyond individual champions. This includes understanding the rights-based dimensions of governance and, specifically, why the inclusive participation of all stakeholder groups including students is not optional but foundational to responsible AI integration.

2. AI policy, academic integrity and student protection

Leaders need to understand how to develop, communicate and maintain policies in relation to AI that are enforceable and regularly reviewed; how generative AI has transformed academic integrity from a plagiarism problem into an authorship problem and what that requires of assessment design; how to build disclosure and transparency requirements into institutional policy; and how to identify and address the specific vulnerabilities of students as the primary users of AI tools and the population most directly affected by AI-mediated decisions in teaching, assessment and student services.

3. Regulatory literacy and quality assurance in the AI era

Leaders need to understand the evolving regional and national AI regulatory landscape. This includes what key regional policy documents adopted at ministerial summits, in particular the *2023 Santiago Declaration,* the *2024 Montevideo Regional Roadmap* and the *2026 Santo Domingo Roadmap*, require and recommend at the institutional level; how national AI strategies and data protection frameworks translate into institutional obligations; and how to position their institution in relation to quality assurance and accreditation requirements. Translating AI governance standards into formal accreditation frameworks is an area of likely regulatory evolution and institutional leaders who build governance capacity now will be better positioned to meet requirements as they mature.

4. AI literacy and curriculum integration leadership

Leaders need to understand how to conduct an institutional AI literacy needs analysis across different staff groups and student populations; how to design capacity development provision that is differentiated by role and function rather than generic; how to build the institutional case for extending AI training beyond the academic core to administrative and technical staff; and how to drive the embedding of AI literacy transversally across curricula through academic planning structures rather than leaving it to individual faculty discretion.

5. Responsible AI deployment (ethics, equity and evidence)

Leaders need to understand how to design and implement minimum monitoring frameworks for AI deployment; how to define indicators that track adoption, preparedness, outcomes and risk; how to identify and mitigate equity risks in AI deployment including which student populations are most exposed to AI-mediated decisions; and how to use evidence to adjust institutional decisions rather than simply report on activities.

Annex II – Survey instrument

Section 1: Institutional profile

Q1. Institution name *(Open-ended)*

Q2. Country *(Open-ended)*

Q3. Region *(Dropdown – 5 UNESCO regions)*

Q4. Your role at the institution

President/Rector/Vice-Chancellor

Vice President/Deputy Head (Academic, Research, or Administration)

Dean or Head of Faculty/Department

Head of Institutional Planning/Strategy

Other: _____

Q5. Size of your institution

Fewer than 5,000 students

5,000–15,000 students

More than 15,000 students

Q6. Type of institution

Public

Private, non-profit

Private, for-profit

Other: _____

Section 2: Enablers and institutional support

Q7. What are the main enablers supporting AI adoption in your institution? *(Select up to 3)*

Leadership commitment

National or regional policies and incentives

Internal champions or taskforces

Strong digital infrastructure

Staff training or capacity-building initiatives

Availability of external partnerships

Funding availability

Open access to datasets and research tools

Robust cybersecurity measures that enhance AI public trust

Other: _____

Q8. Has your institution implemented training or capacity-building programmes related to AI for staff? *(Select all that apply)*

Yes, for academic staff

Yes, for administrative/technical staff

No

Don't know

Q9. Has your institution implemented training or capacity-building programmes related to AI for students? *(Select all that apply)*

Yes, as part of the curriculum

Yes, offered as elective courses

Yes, offered as free workshops

No

Don't know

Q10. Does your institution have a formal strategy that includes digital technologies or Artificial Intelligence (AI)? *(Select one)*

Yes, a formal strategy that includes AI

Yes, a digital strategy but not specific to AI

No formal strategy yet

Don't know

Q11. Has your institution developed specific governance structures or taskforces to oversee AI integration?

Yes, a dedicated office/unit

No, but responsibilities are shared across different departments

No, there is no designated responsibility

Don't know

Q12. What is the composition of the office/unit? *(If Q11 = Yes; select all that apply)*

Faculty or academic staff

IT or technical staff

Administrative or strategic planning staff

External consultants or partners

Student representatives

Other: _____

Q13. Does your institution allocate a specific budget for AI-related initiatives?

Yes, there is a dedicated budget

AI is funded within a broader digital/innovation budget

No specific budget

Don't know

Q14. What are the primary sources of funding for AI activities at your institution? *(Select all that apply)*

Public/national government funding

Institutional core budget

Private sector partnerships or donations

Competitive research grants

Other: _____

Section 3: Institutional guidelines and ethical use of AI

Q15. Does your institution have official guidelines, policies, or frameworks on the use of AI?

Yes, institution-wide

Yes, in specific areas only (e.g. teaching, research)

Under development

No

Don't know

Q16. If guidelines or policies exist, which areas do they cover? *(Select all that apply)*

Academic integrity (e.g. use of AI by students)

Teaching and learning (e.g. faculty use of AI tools)

Research ethics

Administrative decision-making

Data privacy and cybersecurity

Equity, non-discrimination and accessibility

AI procurement or partnerships

Other: _____

Q17. Does your institution have specific guidelines or policies related to academic integrity and the use of AI by students?

Yes, clear and communicated to all students

Yes, but not widely disseminated or enforced

No formal guidelines, but under discussion

No

Don't know

Q18. Have you observed any changes in academic misconduct or integrity since the introduction of AI tools in the classroom?

Yes, increase in reported/plagiarism cases

Yes, more confusion about what constitutes cheating

No significant change

Not monitored

Don't know

Section 4: AI adoption across core missions of higher education

Teaching and learning

Q19. Are AI technologies currently used in teaching and learning at your institution?

Yes

No

Don't know

Q20. What types of AI technologies are used? *(Branched opens if Q19 = Yes)*

Adaptive learning platforms

AI tutors or feedback tools

Learning analytics or predictive analytics

Automated grading or assessment tools

Chatbots or virtual assistants for students

Other: _____

Q21. What are the main objectives for using AI in teaching and learning? *(Branched opens if Q19 = Yes)*

To personalize learning pathways and content for students

To increase student engagement and interactivity

To support early identification of students at risk

To automate grading and feedback processes

To enhance the quality and responsiveness of teaching

To reduce educator workload and administrative burden

To promote innovation in pedagogy and digital transformation

To improve learning outcomes and academic performance

Research

Q22. Is AI currently used to support research at your institution?

Yes

No

Don't know

Q23. In what ways is AI used in research? *(Branched opens if Q22 = Yes)*

Data analysis and visualization

Predictive modelling

Natural language processing or text mining

AI-assisted literature reviews

Research planning and funding forecasting

Other: _____

Q24. What are the main objectives for using AI in research at your institution? *(Branched opens if Q22 = Yes)*

To enhance the quality and depth of research outputs

To accelerate data processing and analysis

To improve the efficiency of literature reviews and knowledge synthesis

To enable more complex or large-scale research projects

To foster interdisciplinary or innovative research approaches

To increase competitiveness in securing research funding

To reduce researcher workload on repetitive or time-consuming tasks

To modernize research infrastructure and practices

Administration

Q25. Is AI used in administrative functions at your institution?

Yes

No

Don't know

Q26. In which administrative areas is AI applied? *(Branched opens if Q25 = Yes)*

Admissions and enrolment

Student support or advising

Human resources

Finance and accounting

Campus security or monitoring

Other: _____

Q27. What are the main objectives for using AI in administrative functions? *(Branched opens if Q25 = Yes)*

To automate routine or repetitive administrative tasks

To reduce staff workload and improve operational efficiency

To support data-informed decision-making and planning

To improve the accuracy and speed of administrative processes

To enhance student services and responsiveness (e.g. through chatbots or predictive tools)

To comply with quality assurance or regulatory standards

To modernize institutional infrastructure and promote digital transformation

Extension services

Q28. Does your institution use AI in its extension services (e.g. community, lifelong learning or industry engagement)?

Yes

No

Don't know

Q29. In which types of activities is AI applied? *(Branched opens if Q28 = Yes)*

Industry or innovation partnerships

Community outreach or engagement

Lifelong learning or continuing education

Technology transfer

Other: _____

Q30. What are the main objectives for using AI in extension services? *(Branched opens if Q28 = Yes)*

To improve outreach effectiveness and relevance for target communities

To personalize content and services for specific external audiences (e.g. adult learners, industry partners, local organizations)

To reduce staff workload and streamline operational processes

To enhance data collection, monitoring, and impact evaluation of extension activities

To expand access to lifelong learning and non-formal education

To strengthen partnerships with industry, government, or civil society

To modernize and position the institution as a leader in digital innovation

Section 5: Key challenges

Q31. What are the main challenges your institution faces in integrating AI across any of its missions? *(Rank from 1 to 8, where 1 = most challenging; select up to 3)*

Lack of financial resources

Limited technical infrastructure or outdated systems

Insufficient staff expertise or training opportunities

Ethical or governance concerns

Resistance to change within the institution

Lack of clear policy or regulatory guidance

Data privacy or cybersecurity risks

Uncertainty about AI's long-term impact on institutional goals

Other: _____

Section 6: Monitoring and evaluation

Q32. Does your institution monitor or evaluate the outcomes of AI implementation?

Yes, we have formal evaluation mechanisms

Evaluation is informal or project-based

No monitoring or evaluation currently

Don't know

Section 7: Vision and future planning

Q33. What are your institution's top concerns regarding AI adoption? *(Select up to 3)*

Ethical risks and bias

Data privacy and cybersecurity

Equity and accessibility

Job displacement

Reputational risks

Legal/regulatory uncertainty

Lack of institutional expertise

Sustainability and cost over time

Other: _____

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Applied Research and Analysis

Working Papers

The UNESCO International Institute for Higher Education in Latin America and the Caribbean (UNESCO IESALC) undertakes applied research on priority higher education issues and translates findings into policymaking-relevant evidence and training opportunities as well as into diverse products for dissemination. Research modalities include desk-based reviews, international surveys, country case studies and comparative analysis, as well as foresight on higher education.

Working Paper 16, entitled AI implementation in higher education in Latin America and the Caribbean, provides a comprehensive evidence base on how higher education institutions in the region are integrating AI across five key dimensions – teaching and learning, research, community engagement, administration and institutional governance. The study draws on a sample of 200 higher education institutions across 19 countries in Latin America and the Caribbean. It provides both a baseline to measure progress and a roadmap for the journey ahead through a series of targeted recommendations for higher education institutions, policy-makers and intergovernmental organizations.

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4 QUALITY EDUCATION

Sustainable Development Goals