TECHNICAL NOTE Nº IDB-TN-3339

Startups x AI

An Overview of Artificial Intelligence Adoption in Latin America and the Caribbean

Lilia Stubrin
Julián Asinsten
Fernando Zornada
Ana Castillo Leska

Inter-American Development Bank
IDB Lab

May 2026

Startups x AI

An Overview of Artificial Intelligence Adoption in Latin America and the Caribbean

Lilia Stubrin
Julián Asinsten
Fernando Zornada
Ana Castillo Leska

Inter-American Development Bank
IDB Lab

May 2026

Keywords: artificial intelligence, startups, Latin America and the Caribbean, innovation, technology adoption, venture capital, digital transformation, AI governance, productivity, entrepreneurial ecosystem.

JEL Codes: G24, M13, O33

Startups x AI

An Overview of Artificial Intelligence Adoption in Latin America and the Caribbean

IDB | LAB

AUTHORS

Lilia Stubrin
Julián Asinsten
Fernando Zornada
Ana Castillo Leska

2026

Graphic Design: Gabriela Krebs (Emigra Design)

CONTENTS

ACKNOWLEDGMENTS

The study was conducted in close collaboration with Cesar Said Rosales (fAIr LAC) and Fernando Vargas (IDB).

The authors would like to acknowledge the invaluable support of the various organizations within the region's entrepreneurial and investment ecosystem in disseminating the survey, and especially to all participating startups for their generosity in sharing information.

ACRONYMS

AI	Artificial Intelligence
GenAI	Generative Artificial Intelligence
G7	Group of Seven
ICT	Information and Communication Technologies
LAC	Latin America and the Caribbean
LLMs	Large Language Models
R&D	Research and Development

I.

EXECUTIVE SUMMARY

This study analyzes artificial intelligence (AI) adoption by startups in Latin America and the Caribbean (LAC), and seeks to understand how they integrate technology into their products, processes, and business models, what benefits they obtain, and what factors facilitate or constrain their AI adoption. The analysis focuses on non-AI-native startups that use AI to leverage innovation, growth, and upscaling, with a special focus on solutions that contribute to social inclusion, environmental sustainability, and reducing productivity gaps in the region.

This work is framed within the knowledge agenda of IDB Lab and the fAIr LAC initiative, both aimed at promoting inclusive digital transformation and responsible AI adoption in the entrepreneurial ecosystem.

This research combines a regional quantitative survey with qualitative case analysis. It explores the technologies adopted —generative AI (GenAI), predictive AI, and automation, the business functions where they are applied, in-house capabilities, perceived benefits, obstacles, and risk management practices. Based on these findings, six startups were selected for case studies in sectors such as health, agriculture, infrastructure, financial inclusion, and services.

Findings have shown that AI has become a key driver for transformation: 85% of the startups surveyed use GenAI tools and 75% use predictive technologies, primarily in marketing, product development, strategy, and research and development (R&D). However, adoption is heterogeneous, and three startup profiles have been identified: developers, which have advanced technical capabilities and proprietary solutions; integrators, which mainly incorporate third-party tools; and experimenters, which are in the early stages of testing. Some of the key benefits stated by businesses are: reduced operating and

R&D costs, development of new AI-based products, and improvements in efficiency and decision-making.

Yet, significant obstacles persist: a shortage of specialized funding, talent gaps, data privacy concerns, and limited adequacy of global models to the local context. Only 12% of startups consider that available solutions fully meet their needs. The study also reveals governance weaknesses: low regulatory knowledge and fledgling risk management practices, along with collaborative networks clustered around technology providers and universities, with limited links to the public sector and investors.

Based on this evidence, the report proposes a set of lines of action that are consistent with the actions of the IDB Group: expanding financing, developing specialized talent, promoting the customization of models to local needs, disseminating sector-specific use cases and strengthening regulatory frameworks so that AI can promote both startup growth and a more inclusive and sustainable development.

II.

INTRODUCTION

This technical note analyzes the adoption of artificial intelligence (AI) technologies by startups in Latin America and the Caribbean (LAC). Its goal is to understand the current dynamics of AI use in these types of businesses, identify the benefits obtained, analyze success stories, and assess those factors that either enable or constrain AI incorporation.

Framed within IDB Lab's fAIr LAC initiative, which promotes responsible and inclusive digital transformation, the study seeks to contribute to the generation of evidence that allows the design of supporting tools, in line with the actual needs of startups in the region, thus strengthening capacities, governance frameworks and conditions for a safe, responsible adoption with an impact on development.

The analysis focuses on startups that, while not conceived as AI-native businesses, have integrated this technology into their products, processes, or business models. Special attention is given to solutions that contribute to improving the living conditions of the region's most vulnerable populations, promoting sustainability, and reducing structural productivity gaps.

Artificial intelligence is "any machine-based system that, with explicit or implicit goals, infers from received information how to generate results, such as predictions, content, recommendations, or decisions that can influence physical or virtual environments". (OECD, 2024)

For the purpose of this survey, the analysis unit will be LAC-based startups that have incorporated AI systems into their production processes, products or services, either through proprietary developments and/or solutions provided by third parties.

The methodological approach combines a quantitative survey with a qualitative case analysis (please see methodological details in Appendix A). The regional survey, conducted in 2025, gathered 107 responses from startups in 14 LAC countries and addressed the following areas: types of technologies adopted (GenAI, predictive AI, and automation), use functions, internal capabilities, perceived benefits and obstacles, and AI risk management practices. Based on these results, six startups were selected for developing case studies, following criteria of diversity across sectors, technological maturity, and AI-adoption profile: developer, integrator, or experimenter.

The report is organized in five sections: an overview of the state of the art in AI adoption in enterprises; the findings of the regional survey; case studies; and, finally, policy recommendations aimed at strengthening AI adoption in a way that combines innovation, productivity and inclusion.

A startup is a "newly formed entrepreneurial venture that seeks to develop a repeatable, scalable, and fast-growing business model built around technology or business model innovations". (Blank, 2010; Freeman and Engel, 2007)

III.

STATE OF THE ART IN AI ADOPTION IN ENTERPRISES

Knowledge about the adoption of artificial intelligence in businesses is still in its early stages and has been concentrated primarily in established firms in developed economies. It is worth mentioning that, most of the available literature predates the expansion of large-scale language models (LLMs), so systematic evidence on the adoption of GenAI remains limited.

This gap stems from the mismatch between the rapid dissemination of technology in the private sector and the capacity of statistical systems to measure it. Indirect indicators, such as labor demand and corporate investment, suggest a significant increase between 2017 and 2020 (Maslej et al., 2024), while business surveys have only recently incorporated specific modules on AI (Calvino and Fontanelli, 2023). In parallel, ad hoc surveys aimed at capturing this phenomenon are beginning to emerge, among which the present study is included.

Evidence on AI adoption in startups is even scarcer. While there is consensus that AI is a general-purpose technology with high transformative potential, studies on its impact on entrepreneurship are still limited (Chalmers et al., 2021; Shepherd and Majchrzak, 2022; Giuggioli and Pellegrini, 2023; Sammet et al., 2024).

Based on this framework, this section summarizes the main available lessons learned from the adoption of AI in established enterprises and startups.

Adoption of AI in enterprises remains limited. Available evidence shows that AI adoption rates remain low in most countries, with single-digit rates in many cases. This low penetration rate is observed in both developed economies and LAC countries (and other developing countries), although with significant levels of heterogeneity. In the United States, only 6% of enterprises report some use of AI (McElheran et al., 2024), a figure almost identical to that estimated for 2020 (Zolas et al., 2020). In Europe, the average is 8%, with Denmark and Finland leading the way (15%) and France and Italy lagging behind at between 5% and 6% (Eurostat, 2023). Additionally, Germany reports a rate of 7% (Czarnitzki et al., 2023). The LAC region is no exception to this trend, with the following figures: 6% of manufacturing companies in Colombia (Herrera Giraldo et al., 2024), and 13% of companies in Brazil (Brazilian Network Information Center & CGI, 2022). For the time being, rather than being a massively widespread phenomenon, AI seems to be more of an "archipelago of experiences".

When it comes to AI adoption, size matters. Large firms have the data, infrastructure, and capacity to attract talent, while small firms face upscaling barriers (OECD/BCG/INSEAD, 2025). In the United Kingdom, adoption amounts to 34% in medium-sized companies, compared to 15% in small enterprises (Evans and Heimann, 2022); in Japan, it can increase from 10% to 48% among companies with 100 to more than 2,000 employees (MIC, 2021). However, alongside this leadership by large companies, a second phenomenon is emerging: some startups and young firms are placing AI at the core of their value proposition and exhibit highly intensive specialized hiring (Calvino et al., 2022). Colombia illustrates this duality: greater adoption rates among large companies coexist with a dynamic role for early-stage entrepreneurship (Herrera Giraldo et al., 2024).

AI adoption varies significantly across sectors. The most data-intensive sectors, with a higher degree of digitalization or exposure to technological change, exhibit higher adoption rates. This is the case for the Information and Communication Technologies (ICT) sector and financial, consulting, and legal services. In France, the ICT sector has the highest proportion of companies using AI, especially those that develop their technologies in-house (Calvino and Fontanelli, 2023b). In the United Kingdom, approximately 40% of adopting companies belong to ICT and professional services sectors (Calvino et al., 2022). In G7 countries, ICT and financial and insurance services, legal, engineering, design, consulting, and advertising stand out with high adoption rates —all of them being sectors with high exposure to technological change and heavy data use (OECD/BCG/INSEAD, 2025). In contrast, traditional or less digitalized sectors face more barriers and adopt AI at a lower proportion, although with some exceptions. Sectors with medium adoption rates show some dynamism, partly due to the increasing availability of clinical, administrative, and industrial data. This is the case of health and information sectors in the United States, which have adoption rates close to 12%, a figure higher than the overall average of 6% (McElheran et al., 2024). In contrast, more traditional sectors face greater obstacles. Even in G7 countries, the manufacturing sector reports more frequent obstacles to AI adoption, attributable to a less established tradition of data use and an approach that tends to be more product-oriented than information-oriented (OECD/BCG/INSEAD, 2025).

AI adoption varies significantly depending on the business function. Evidence shows that companies —including startups — tend to incorporate AI in specific business functions where technology can deliver greater economic value, improve operational efficiency, or facilitate the customization of products and services. In contrast, other areas show lower adoption rates, whether due to technical, regulatory, or cultural barriers. R&D is one of the functions where AI use is most common and consistent across sectors, while marketing, sales, and product development lead in GenAI deployment (McKinsey, 2025). A survey on companies from G7 countries and Brazil found that the proportion of AI spending within the R&D budget is directly related to the perception of AI as critical to the business: while only 38% of companies allocating up to 10% of their R&D budget to AI consider it critical, the percentage increases up to 87% among those allocating more than 30% (OECD/BCG/INSEAD, 2025). Meanwhile, in Germany, approximately 56% of companies adopting AI use it to automate processes, 34% for data analysis, and 22% for interacting with customers (Czarnitzki et al.,

(1) United States, Canada, France, United Kingdom, Germany, Italy and Japan.

2023), thus reflecting a focus on operational efficiency. Human resources, on the other hand, shows the lowest adoption rates due to ethical and regulatory concerns (OECD/BCG/INSEAD, 2025).

AI adoption does not follow a single path across enterprises. AI adoption does not follow a single pattern, but rather is based on mixed strategies that combine in-house capability development with the acquisition of external solutions. The relative weight of each approach varies according to company size, sector and age, and its organizational capabilities.

International evidence shows that large and technology-based firms predominantly favor an in-house AI development approach, supported by R&D investments and the hiring of specialized talent.

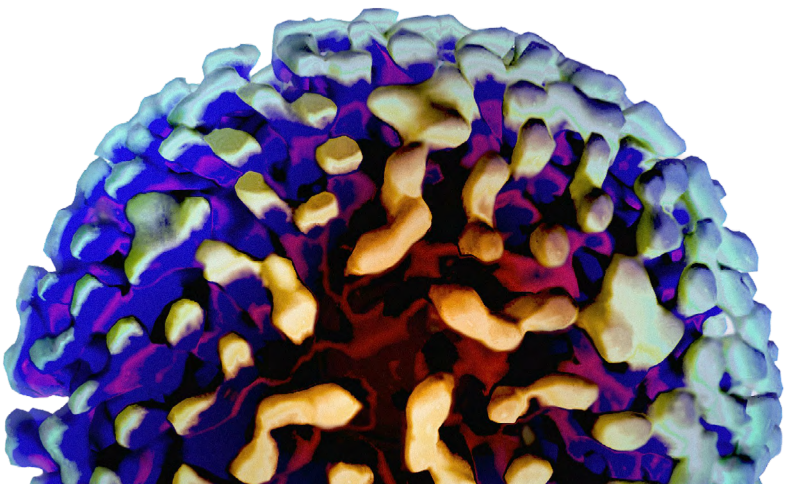
A survey of more than 1,000 medium-sized and large enterprises in G7 countries and Brazil indicates that more than 70% of manufacturing and ICT firms conduct AI R&D for internal use, and more than 60% hire new staff to develop such technologies (OECD/BCG/INSEAD, 2025). However, these enterprises also adopt hybrid approaches, with between 53% and 64% of them complementing in-house development with the purchase of external solutions (OECD/BCG/INSEAD, 2025). In-house development is often associated with organizational transformation processes. According to McKinsey (2025), large companies are redesigning workflows and creating AI-specific governance structures, including talent retraining and the creation of executive roles. Evidence suggests that delegating adoption solely on technology departments is insufficient, and that effectively leveraging AI requires leadership from senior management and sustained investment in internal capabilities.

In contrast, smaller or more traditional companies predominantly acquire external solutions.

In France, 9.9% of companies with more than 10 employees use third-party AI applications that they have purchased, compared to only 3.2% that develop their own solutions (Calvino and Fontanelli, 2023b). In Colombia, among industrial firms adopting AI, only 2.2% develop their technology in-house, while 4.4% rely on third-party solutions (Herrera Giraldo et al., 2024). These patterns reflect a greater reliance on external markets for AI technologies in contexts with lower technological density and more limited internal capabilities.

Evidence on the role of the ecosystem in AI adoption is still incipient, although participation from universities and research centers can be observed in developed countries and Brazil. While literature on innovation has historically emphasized the importance of links between companies and ecosystem actors —such as universities, public R&D centers, startups, and large corporations— studies exploring these links, specifically in relation to AI adoption, remain limited. Available evidence suggests that these links are relevant, especially among companies with a strong focus on AI R&D. A key driver for such collaborations is access to talent. A total of 76% of companies that partner with academic institutions have hired AI graduates in the past year, suggesting that university-business interaction serves a dual purpose, facilitating technology adoption and enriching the productive sector with human capabilities (OECD/BCG/INSEAD, 2025). Despite these indications, empirical evidence on the role of the ecosystem in AI adoption remains scarce, particularly regarding startups, small and medium enterprises (SMEs), and developing countries. There is a lack of systematic analysis of the quality, intensity, and modalities of such interactions, as well as their effective impact on the processes of adoption and ownership of AI technologies.

Relevance of entrepreneurial profiles of startup founders for AI adoption. Academic background and prior entrepreneurial experience are critical factors for AI adoption in startups. McElheran et al. (2024) found that, in a study of over 4 million firms in the United States, AI use is more significant among entrepreneurs with more formal training and prior experience. This finding suggests that the adoption of advanced technologies like AI in startups also depends on the human and cognitive capital of their founders.



IV.

AI ADOPTION IN STARTUPS IN LAC: MAIN SURVEY FINDINGS

This section presents the main findings of the survey on AI adoption by startups in LAC. Data paint a clear picture: AI is already becoming part of the DNA of many startups in the region, but not in the same way nor with the same results. This section presents the main findings of the regional survey and gives evidence on: first, how AI is perceived as a competitive advantage; second, which technologies are leading the way (GenAI and predictive AI) and for what types of activities they are being used; and third, why adoption is heterogeneous, showing three distinct profiles (developers, integrators, and experimenters).

The section also delves into benefits and obstacles, the need for tailoring to the local context, links with ecosystem actors, levels of regulatory knowledge and risk management practices, and further concludes with concrete signs of the type of support that startups demand for scaling to a more effective and responsible adoption of AI.

4.1 AI as a competitive factor: a new frontier for competing, with uneven adoption rates.

For most startups in LAC, AI is no longer a technological promise, but a new competitiveness frontier. The survey findings show that AI is increasingly perceived as an engine of sectoral transformation and an enabling condition for sustaining and scaling competitive advantages. Half of the surveyed companies (50%) believe that AI is "already actively transforming" the sectors in which they operate and is consolidating as a key factor for competing, while 28% identify it as a still-embryonic technology, but with high strategic potential for those who manage to become early-adopters. In this context, skepticism is marginal: only two startups in the sample —one in the services sector and the other in agriculture— have reported not perceiving great potential in its incorporation.

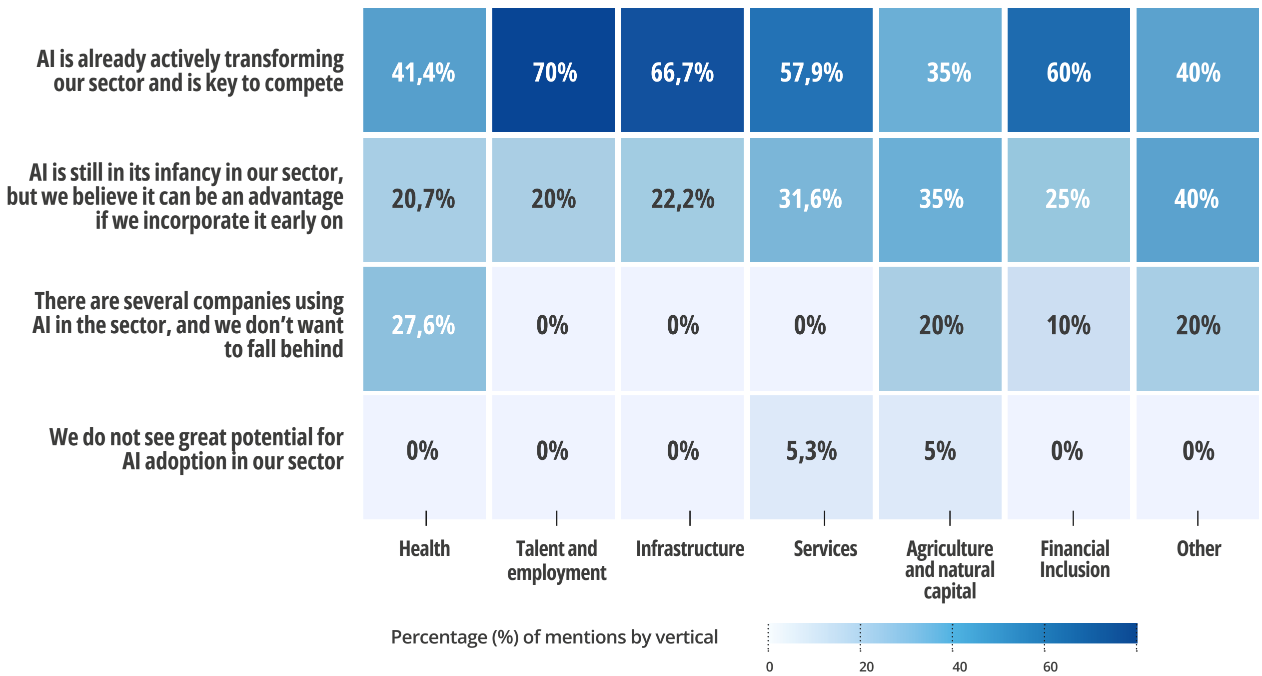
Beyond these differences in intensity, perception of AI as a competitiveness driver is remarkably cross-cutting among sectors, suggesting that technology is being internalized as a horizontal strategic capability, rather than a tool limited to specific niches. However, relevant nuances are observed in the speed and depth of this transformation. Among troubleshooters working in talent and employment (70%), infrastructure (66.7%), and financial inclusion (60%), there is a more advanced perception of an ongoing change, consistent with the visible adoption of automation solutions, matching algorithms, predictive maintenance, and customized financial services. At the opposite end of the spectrum, those focused on agriculture and natural capital are in a more anticipatory phase: only 35% perceive an active transformation, although a similar proportion recognizes the high potential of AI if structural gaps in data, infrastructure, and productive heterogeneity can be overcome. In healthcare, perceptions are more distributed: clear signs of transformation (41.4%) coexist with a strong competitive pressure to accelerate adoption (27.6%), reflecting an environment where the adoption of AI-based diagnostic tools is already redefining performance standards. Among those focused on services, this perception is mixed, consistent with the diversity of activities within the sector.

Overall, findings suggest that AI is perceived by startups in the region not only as an emerging technology, but as a new competitive language, the early adoption of which can amplify gaps between those who manage to integrate it strategically and those who fall behind in capabilities, productivity, and innovation.

This study adopts OECD's (2024) definition of AI, which conceives AI as a set of systems capable of generating results —predictions, content, recommendations, or decisions— from the analysis of information, influencing physical or virtual environments. From this perspective, AI is not a single technology, but rather a set of complementary capabilities that can be deployed for different purposes within organizations. There are different types of AI that can be used for different purposes (Table 1).

(2) "An AI system is a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment." (OECD, 2024)

Figure 1 - Perception of dynamism in AI adoption in the market (as % of total surveyed companies, by vertical)



4.2 Among startups adopting AI to create, analyze, and decide, generative and predictive technologies prevail

Table 1 - Main types of AI technologies and their functions

TECHNOLOGY	FUNCTION
Generative models (text, image, audio, video)	They create new content based on instructions or examples. For instance, they can automatically write texts, generate images, compose music, or generate videos.
Language/Text Processing (NLP)	It allows computers to “understand” and work with human language. It is used, for example, to analyze opinions, summarize documents, or answer questions.
Computer vision	It teaches machines how to “see” and interpret images or videos. This is applied, for example, to object recognition, reading text in images (OCR), or detecting visual patterns.
Audio and voice	It facilitates interaction through sound. It can recognize and transcribe the human voice, identify who is speaking, or analyze tones and emotions in recordings.
Structured Data / Classical ML	It analyzes large volumes of numerical or tabular data to detect patterns and make predictions, for example, about sales, risks, or user behavior.
Robotics and automation	It combines AI and mechanical systems to perform tasks autonomously or with minimal human intervention, such as assembling, moving, or classifying products.

The data show that startups in LAC are rapidly incorporating these capabilities, though in a selective way. Adoption is clearly concentrated in two major technology families: GenAI and predictive AI. 85% of the startups analyzed report using GenAI tools, while three out of four (75%) apply predictive AI technologies, such as natural language processing, computer vision, or machine learning models on structured data. In contrast, the use of robotics and automation is still limited: only 27% report using them, with a strong concentration in a few sectors.

Beyond the type of technology used, a consistent functional pattern emerges: AI is mainly integrated into those business areas where it has the greatest capacity to expand cognitive capabilities, that is, to create, analyze, and decide.

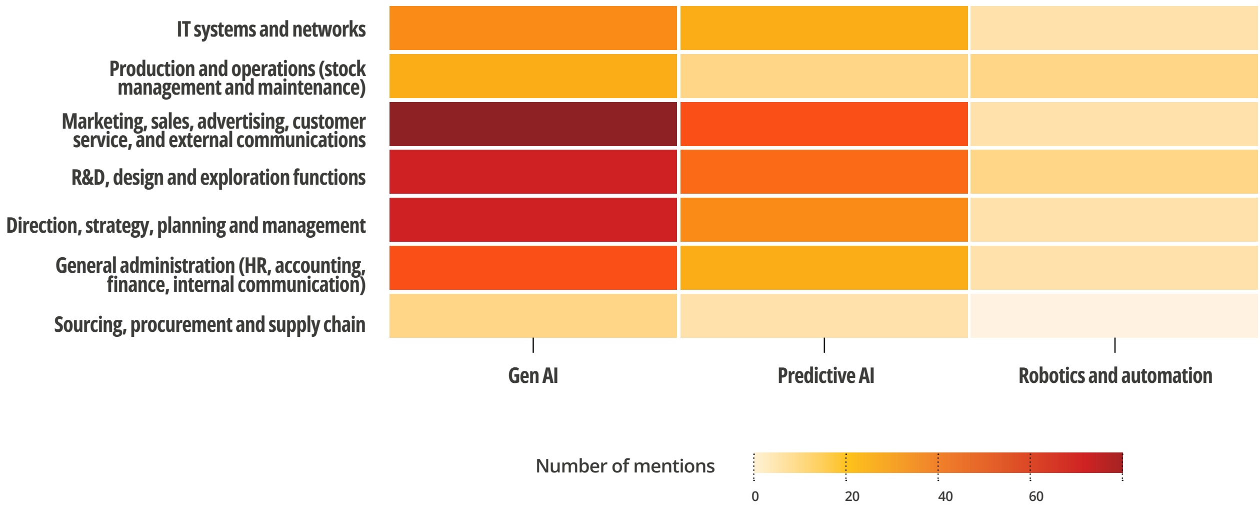
Startups are using AI primarily to interact with customers, plan, design products, and support strategic processes, but much less to perform operational, logistics, or administrative tasks.

In the case of generative AI (GenAI), its use spans virtually all business functions, but is concentrated in marketing, sales, customer service, and external communications (62%), management and strategy (59%), and R&D and design (57%). Administrative functions show medium adoption rates, while production, procurement, and logistics continue to lag significantly behind, using less than 20%.

On the other hand, predictive AI shows a very similar pattern, although with a more analytical focus: it is mainly used in marketing and customer service (42%), R&D (39%), and management and strategy (35%), reflecting its role in supporting data analysis, planning, and innovation. Once again, operational functions are the least digitalized functions, with adoption rates below 15%.

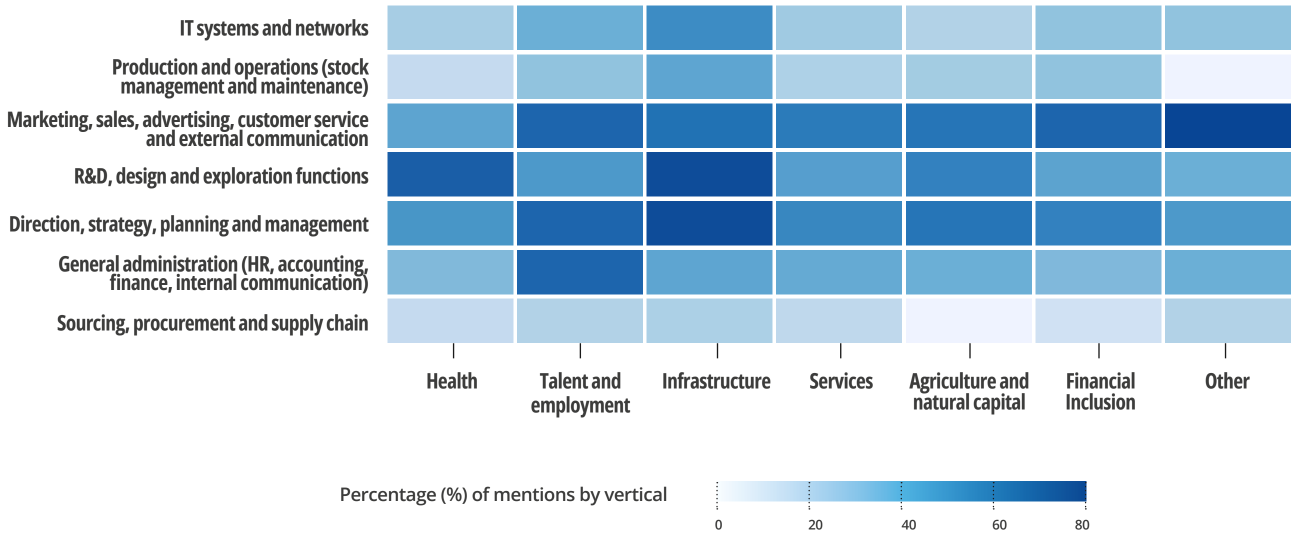
Robotics and automation, meanwhile, remain in their infancy. Only one in four startups uses them, and when they actually do, it's for specific applications in R&D or production processes, without significant integration into the rest of the business functions.

Figure 2 - AI use by technology and business function



This pattern is replicated, with some nuances, at a sector level. In health, infrastructure, agriculture, financial inclusion, and services, GenAI is systematically oriented towards research, design, planning, communication, and management functions, with little presence in physical or logistics operations. AI thus appears as a horizontal technology in sectoral terms, but with a clear functional bias towards areas of greater cognitive value.

Figure 3 - GenAI use by application area and business function



Key highlights:

- In Health, GenAI adoption is primarily focused on research, development, design, and exploration (72%), which are the core of the sector's activity, followed by management and administration (52%). Its presence in marketing and communications (45%) is moderate, while operational and administrative functions exhibit lower levels (between 14% and 34%).
- In Agriculture and natural capital, GenAI shows similar levels of use for the most widespread functions: 65% of the startups analyzed use them for management and strategy, and 65% for marketing and communication, and 60% for R&D tasks. Production (25%) and IT systems (20%) show embryonic use, while supply exhibits virtually no adoption.
- In Infrastructure, GenAI appears widely extended in management functions (78%), R&D (78%) and marketing (67%), which suggests that application is oriented towards optimizing projects, planning and technical communication, in line with the sector profile.
- In Financial Inclusion, the pattern replicates the bias towards market functions: marketing, sales, and customer service (70%) lead in GenAI use, followed by management (60%) and R&D (45%). Administrative and technological areas (30–35%) show average adoption, while supply barely reaches 10%.
- In Services, GenAI is applied in a more cross-cutting way, with greater presence in marketing (63%) and management (58%), but also with relevant levels in R&D (47%) and administration (42%), reflecting a broader functional integration.
- In Talent and Employment, GenAI is used with relatively high intensity in marketing, management and administration (70% in each case), which suggests that its use is oriented towards communication, planning and management of recruiting or training processes.

These findings are aligned with international evidence, which also shows greater adoption of AI in strategic, innovation and market functions, such as marketing, sales, R&D and business management, and slower dissemination in administrative and operational functions, due to technical, regulatory and cultural barriers (OECD/BCG/INSEAD, 2025; McKinsey, 2025).

From a strategic perspective, the message is clear: startups are not primarily using AI as an automation tool, but rather as a cognitive infrastructure to support how they innovate, how they make decisions, and how they engage with their markets. The most profound productive transformation —the kind that impacts physical processes, operations, and value chains—remains, for now, a less explored domain.

4.3 Three AI adoption profiles: developers, integrators, and experimenters

The survey identifies three distinct AI adoption profiles among startups in the region, defined by their technology strategy, in-house capabilities, and use of enabling factors such as data, infrastructure, and talent (see Table 2): AI developers, integrators, and experimenters. Rather than static categories, these profiles represent maturity trajectories in the way in which startups adopt AI as a strategic asset.

- AI-developers represent the group with the highest degree of technological autonomy. In these cases, AI is at the core of their business model: the main product or service is an AI-based solution developed in-house. These startups have robust R&D teams, consolidated technical leadership, and clear technology governance, typically through co-leadership between the CEO and CTO. Their AI adoption is both deliberate and structured: they define objectives, allocate specific resources, and build their own data and infrastructure capabilities. They often combine cloud environments with proprietary servers, manage their data systematically, and maintain high levels of technical expertise. These firms account for 30% of the sample.
- AI-Integrators represent an intermediate stage. They incorporate AI into their products and processes, but it is not the core of their value proposition. Their strategy is intentional, though less formalized: they recognize the importance of AI and experiment with different use cases, but without a fully structured planning. They combine moderate in-house capabilities with third-party solutions, primarily use cloud infrastructure and APIs, and rely more heavily on technology providers. Leadership is typically concentrated on the CEO, while technical teams play an implementation role rather than a strategic design role. These firms account for 55% of the sample.
- AI-experimenters are those startups in an early adoption phase, characterized by

testing and learning. Their technical capabilities are limited, with little specialized talent and heavy reliance on third-party services. They lack an explicit AI strategy, and their use is geared towards ad hoc testing rather than systematic integration. In terms of data, uncertainty prevails: many of them collect information without clear evaluation or quality processes, which limits their ability to scale AI-based solutions. These firms account for 15% of the sample.

Table 2. AI adoption profiles in LAC startups

DIMENSION	DEVELOPERS	INTEGRATORS	EXPERIMENTERS
Strategy	They have a formalized strategy with specifically defined goals, budget, and staff.	They have a strategic intent, but they lack full formalization.	They lack a specific strategy, although some have expressed their interest in developing one.
Leadership	Co-leadership between CEOs/founders and CTOs; close coordination between business and technology.	CEO-centered leadership.	CEO leadership without a consolidated technical structure.
Talent	High specialization in AI (≈4 experts on average).	Average AI capabilities (≈2.5 experts).	Limited AI capabilities (≈1 expert or less).
Infrastructure	Hybrid and diversified: they combine both cloud infrastructure and proprietary servers.	Reliance on cloud infrastructure and APIs; less internal control.	Complete reliance on external services, with no infrastructure of their own.
Data management	Data are systematically collected and evaluated; high reliability of data quality.	Data are collected in key areas, but without systematic evaluation.	Uncertainty about data quality and availability; informal management.
Adoption efforts	Based primarily on internal R&D.	They combine their own efforts with third-party solutions.	Limited or non-existent.

Taken together, these three profiles reflect varying levels of organizational ownership of technology. While developers use AI as a core competitive asset, integrators employ it as a tool for improvement and differentiation, and experimenters as a learning environment. From a strategic perspective, the main challenge is not only to increase adoption, but to facilitate the transition from experimenter profiles to more integrated and autonomous models, strengthening capabilities in talent, data, governance, and infrastructure.

4.4 Leadership of experienced founders is associated with deeper AI adoption

International evidence suggests that AI adoption depends not only on corporate technological or organizational capabilities, but also —and decisively— on the leadership profile of those who found and run companies. A study of more than four million firms in the United States shows that AI use is significantly higher among entrepreneurs with higher education levels and prior experience, reinforcing the idea that the adoption of state-of-the-art technologies is ultimately a matter of human and cognitive capital (McElheran et al., 2024).

This pattern is replicated in the case of the LAC startups analyzed in this study. Developers, the enterprises most advanced in terms of AI adoption, are mostly led by founders with greater work experience: 50% have at least one founder with more than 10 years of entrepreneurial experience, and 75% have more than 7 years. A similar profile is observed among integrator startups, where 55% of founders have more than a decade of experience, and 77% have more than 7 years. In contrast, experimenter startups exhibit younger leadership or with shorter track records: only 38% of their founders have more than 10 years of experience. In these cases, AI tends to be incorporated in a more experimental and less strategic way, suggesting a direct relationship between entrepreneurial experience and the ability to translate technology into business decisions.

From a strategic perspective, these results reinforce a key message: AI adoption isn't achieved solely through infrastructure investments or access to tools, but rather through leadership capable of interpreting, prioritizing, and governing technology. In LAC, where access to specialized talent remains limited, strengthening the capabilities of founders emerges as a critical lever for accelerating the digital transformation of the entrepreneurial ecosystem.

4.5 Internal knowledge gaps: AI moves faster than organizational capabilities

The analysis of internal AI knowledge among startups in the region reveals a clear sign: AI adoption is not homogeneous across organizations. Significant gaps exist between technical teams, sales departments, and management levels, and these differences increase or decrease depending on the level of technological maturity of enterprises.

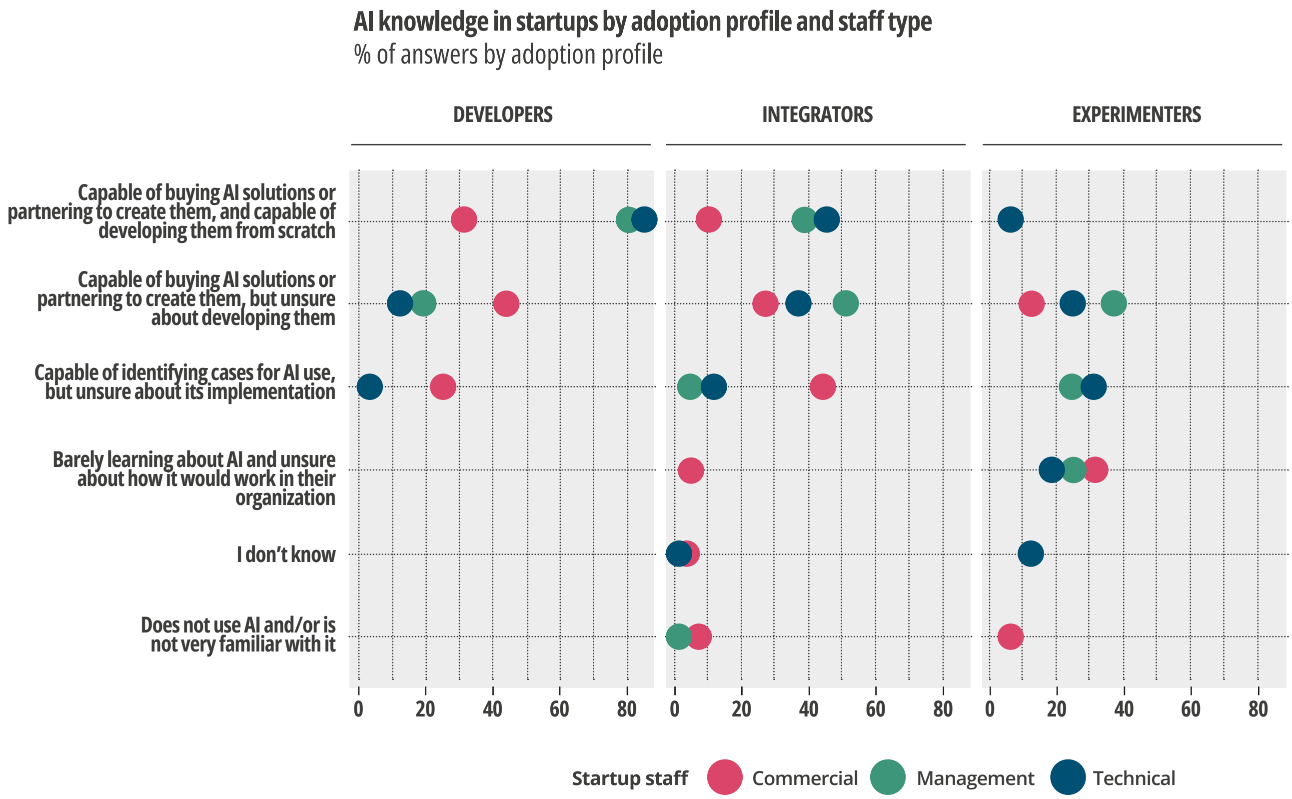
- In AI developer startups, where AI is at the core of the business model, there is a high level of technical and managerial expertise, but there is a significant lag in commercial areas. While 84% of technical teams and 81% of management teams consider themselves capable of developing or adapting AI solutions in-house, only 31% of commercial teams report being capable of this. However, 44% of these teams can identify cases for AI use, but are unable to implement them. This gap suggests that, even in the most advanced companies, technological knowledge does not always translate into market capabilities.

- In AI integrator startups, the pattern is more heterogeneous, with greater reliance on external actors. Less than half of the technical teams (46%) feel capable of developing or customizing solutions, and more than one third rely on purchasing them or partnering for this purpose. At a management level, only 39% report having internal capabilities, while 51% rely on third-party solutions. The most critical gap is observed in business areas: 44% can only identify use cases, and barely 10% consider themselves capable of developing or customizing solutions. This group displays the greatest gap between strategic AI understanding and operational ownership.

- AI experimenter startups exhibit a different pattern: they have low levels of knowledge across all functions, but with less pronounced internal gaps because they are all starting from an embryonic baseline. Only 6% of technical and management teams consider themselves capable of developing solutions, while more than 60% are still in the learning phase. Commercial teams are the ones most lagging behind: 31% report being “in the learning process”, and almost 20% are unfamiliar with AI.

Overall, these findings reveal a structural tension: AI is first incorporated into technical and strategic cores, but its further dissemination into commercial and operational functions is much slower. This points to a key challenge in digital transformation: the gap is not only technological, but also organizational and cognitive. Without cross-cutting capabilities, especially in those areas that link technology with markets, AI risks being confined to internal laboratories, failing to fully translate into economic value, scalability, and impact.

Figure 4 - AI knowledge in startups by adoption profile and organizational role



4.6 Room for innovation: global AI does not automatically fit into local contexts

The study findings show a compelling picture: for most startups in LAC, off-the shelf AI solutions available on the market do not strictly meet their needs. Only 12% consider standard tools to be a good fit for their requirements, revealing a significant gap between the global technological supply and the operational reality of startups in the region. This gap is not solely due to technical constraints, but is rather the result of two types of structural mismatches:

The need to customize solutions to production processes and product characteristics. Nearly 40% of startups report that they require some degree of customization in order to integrate AI into their processes or products. This trend is observed almost consistently across different sectors. This includes regulatory adjustments, retraining models with proprietary data, customization to obtain highly specialized products, and, in many cases, scalability constraints that render high-cost, standardized solutions inefficient.

The need for customizing solutions to the local context. Nearly three out of ten startups (30%) report that they require AI models to be customized to local conditions. This demand becomes especially relevant in sectors such as health, agriculture, financial inclusion, and infrastructure, where environmental, social, and cultural conditions are determining factors. Startups cite constraints in training data for adequately representing language variations (including regional variations of Spanish or indigenous languages), availability of local data (environmental, geographic, biological, or health-related), and knowledge of cultural practices and social contexts specific to their region.

Table 3. Types of customization needs for AI solutions among LAC startups surveyed

TYPES OF CUSTOMIZATION NEEDS	NUMBER OF RESPONSES	% OF TOTAL RESPONSES
Some degree of customization is required to integrate AI solutions into our processes, but this is not due to local context factors	42	39%
Customization is required, mostly due to specificities of the local context that are not represented in training data (e.g., environmental characteristics, languages, social contexts)	32	30%
Available solutions suit our needs well; no customization is required in our case	13	12%
I don't know	3	3%
Other (please specify)	7	6%
No answer	10	10%

This pattern becomes stronger among startups that are more advanced in their adoption of AI. Among AI developers, over 75% require models to be customized to their local context or production processes. AI-integrator startups exhibit similar dynamics, with greater needs for adjustments to products and processes, while AI-experimenters have more limited demands, although even in this group only one out of four reports that no customization is needed.

Figure 5 - Customization needs by adoption profile and efforts made

	ADOPTION PROFILE			EFFORTS				
	Developers	Integrators	Experimenters	Software/ hardware procurement	R&D in AI	New staff	Management or AI team	Systems customized by third parties
Customization for process integration	38%	44%	25%	40%	57%	21%	14%	36%
Customization to local context	41%	29%	12%	38%	69%	47%	44%	38%
No customization needed	3%	14%	25%	23%	62%	23%	8%	31%
Other/I don't know	9%	8%	12%	20%	50%	50%	50%	30%
No answer	9%	5%	25%	10%	20%	10%	20%	20%

From a strategic perspective, these results reveal a central tension: AI is global in its design, but deeply local in its implementation. The lack of adequacy of existing models can act as a barrier to adoption, but at the same time, it opens up a clear space, paving the way for innovation. Where global solutions fail to reflect the conditions of the region's environment, opportunities emerge to develop local capabilities, generate new models, strengthen R&D, and build a more relevant, contextualized AI with greater impact on the region's productive, social, and environmental challenges.

4.7 Links and collaboration networks: how AI adoption profiles in startups define their position within the ecosystem

Evidence shows that the way in which startups engage with their environment varies significantly, depending on their AI adoption profile. Rather than a homogeneous phenomenon, the adoption of this technology is associated with distinct patterns of integration into knowledge networks, markets, and infrastructure (Figure 6).

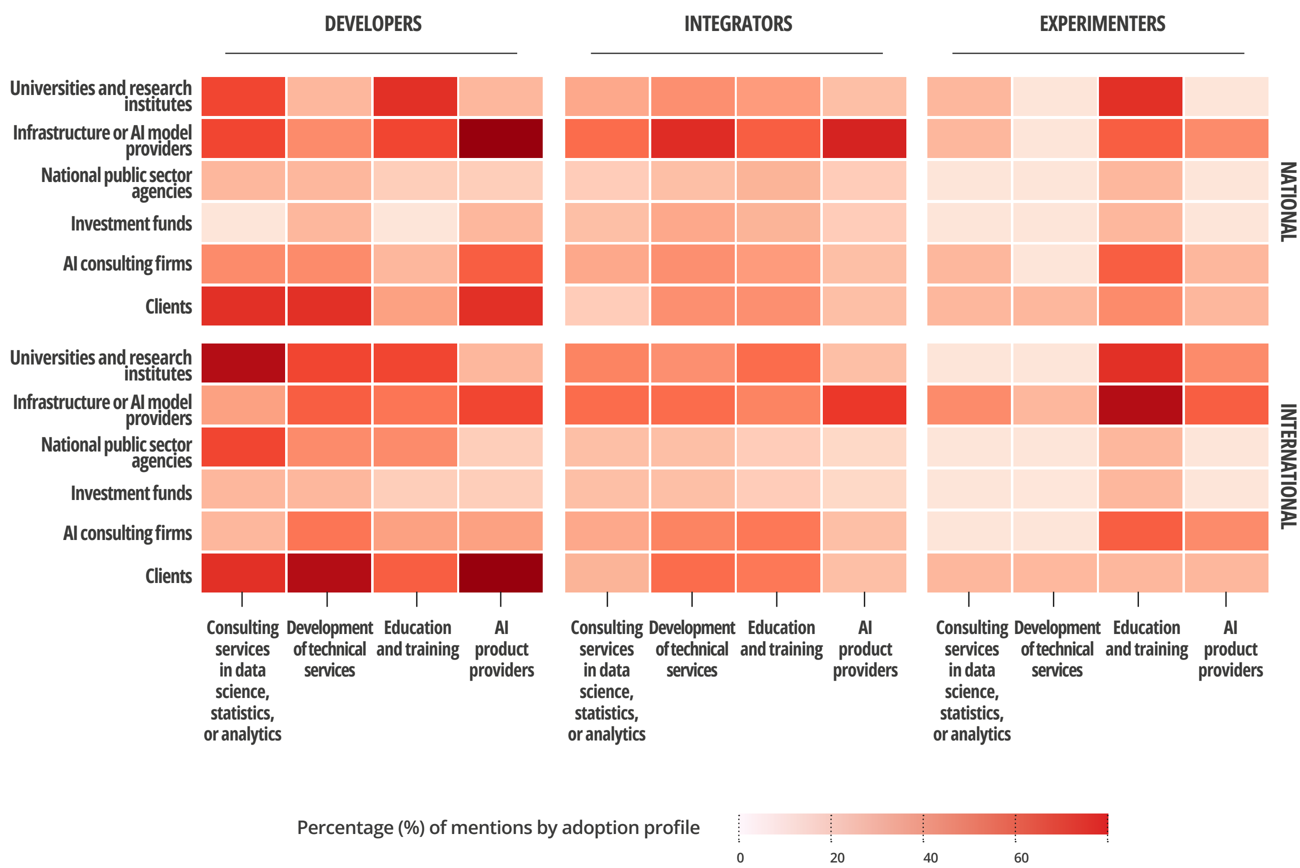
Overall, startups in the region selectively integrate into networks with industry and knowledge actors, while their links with the public sector and institutional investors remain weak or sporadic. The actors exhibiting the densest relationships are national and international providers of AI infrastructure and models, who play a central role as technological enablers, especially for AI developer and integrator startups. These relationships extend beyond the provision of tools to include technical support, training, and skills transfer.

- **AI developer startups exhibit the broadest and most diversified networks in the ecosystem.** Within this group, innovation thrives in highly collaborative environments, where technical autonomy is complemented by strong links with clients and universities. 56% maintain relationships with domestic clients and 44% with international clients, combining the provision of AI solutions, technical services, and specialized consulting. Similarly, 41% report links with domestic universities and 34% with international universities, primarily for training, advising, and joint development purposes. These networks reflect an advanced learning and co-creation rationale, articulated with international knowledge networks.

- **AI integrator startups exhibit more functional and less intensive links.** Around 44% of these startups interact with domestic clients and 28% with international clients, with similar patterns in their interaction with universities. In these cases, their links are primarily focused on education, training, and the adoption of external solutions, rather than co-development processes. Their relationship with international technology providers —particularly for cloud platforms and pre-trained models— is key to integrating AI into their products and processes, although with less technological ownership. In this profile, networks operate more as channels for the transfer of capabilities than as spaces for joint innovation.

- **AI experimenter startups exhibit the lowest levels of engagement.** Their interactions are concentrated almost exclusively with infrastructure providers and external consultants, for basic training or early-stage implementation purposes. Their links with universities are infrequent, and international connections are virtually nonexistent, thus limiting their access to advanced knowledge networks.

Figure 6 – Relevance of links by actor type and objective, by adoption profile



One cross-cutting feature to all profiles is the low presence of the public sector among collaboration networks. Only 18% of startups report any type of interaction with government agencies, mainly concentrated among software developers (around 30%). Similarly, venture capital funding does not appear to be a key player: less than 10% have links with local funds and slightly more than 10% with international funds.

These findings reveal a structural trend: AI adoption in the region is driven more by markets and technology providers than by public policies or the role of investors. The absence of public and financial actors in the networks limits the possibilities for scaling solutions, building capabilities, and creating sustainable innovation pathways. Therefore, strengthening these links emerges as a key condition for transforming AI adoption into a genuine development process in the ecosystem.

4.8 The regulatory gap: most startups adopt AI without knowledge of the regulatory framework

The study findings reveal a worrying trend: there is a widespread lack of knowledge of the regulatory framework for AI use among startups in LAC. Overall, 63% of companies report they are unaware of the existence of any specific regulations (37%), or believe that such regulations do not exist in their country (26%). Only 10% claim to know the regulatory framework very well, while another 26% report to have a general understanding.

This pattern is repeated across almost all verticals, reflecting both the nascent nature of regulatory frameworks and the limited institutional dissemination of information about their scope and content. The gap is particularly marked in the Agriculture and Natural Capital sector, where 70% of startups are unaware of the existence of regulations and only 5% report having a good understanding thereof. In contrast, sectors such as Infrastructure, Services, and Financial Inclusion show somewhat higher levels of familiarity, with between 30% and 45% of startups reporting general or advanced knowledge, likely due to their greater exposure to digital, financial, or data regulatory environments.

Table 4 - Knowledge of AI regulatory frameworks, by application sector or area (in percentages)

	Health	Talent and employment	Infrastructure	Services	Agriculture and natural capital	Financial Inclusion	Other
There is a regulatory framework in place and I am highly knowledgeable about it	10%	20%	11%	11%	5%	5%	0%
There is a regulatory framework in place and I have a general understanding of it	31%	20%	33%	21%	5%	35%	40%
I am not aware of the existence of a regulatory framework for AI use in my country	34%	20%	22%	32%	70%	20%	60%
There is no regulatory framework in place for AI use in my country	21%	30%	33%	37%	15%	40%	0%
No answer	3%	10%	0%	0%	5%	0%	0%

Differences by adoption profile are relatively small. Even among developers, the most advanced startups in terms of AI adoption, only 19% report being familiar with current regulations, while among AI integrators and experimenters, the lack of awareness is even greater. This suggests that the problem is not limited to a lack of technical capabilities, but rather to a structural information asymmetry between emerging governance frameworks and leading actors in technology adoption.

This knowledge gap in regulatory matters poses a systemic risk: AI is being deployed faster than the institutional capacity to support it, both in terms of regulatory aspects and ownership by the private sector. The lack of regulatory clarity can act as a barrier to responsible adoption, weaken user and investor confidence, and limit the scaling of AI-based solutions. Therefore, strengthening regulatory dissemination, understanding, and dialogue emerges as a critical condition for building a more reliable, inclusive, and sustainable AI ecosystem in the region.

4.9 The main benefits of AI adoption vary among adopter types

The study findings show that AI adoption generates tangible benefits for startups in the region, although its nature and intensity vary significantly depending on adopter profiles. Overall, AI translates into cost reductions, improvements in operational efficiency and the development of new solutions, but these impacts are much more pronounced in companies with greater technological capabilities.

- Among AI developer startups, AI acts as a driving force for innovation and expansion. In this case, 75% report having developed new applications that incorporate AI solutions, reflecting a focus on use being oriented to value creation and technological differentiation. Furthermore, one third of these companies report increased sales (34%) and access to new markets (31%), along with reductions in operating and R&D costs (38% in both cases). In this group, AI not only improves efficiency but also enables new opportunities for growth and competitive positioning.
- AI integrator startups show a different pattern, more focused on efficiency. The most frequent benefit is reduced operating costs (58%), followed by reduced R&D costs (37%). However, almost half of these startups (49%) also report having developed new products or services that include AI, indicating that, even when technology is not the core of the business model, it can leverage innovation incrementally.
- In contrast, AI experimenter startups report more modest and primarily operational benefits. Here, impacts are concentrated in small efficiency improvements or cost reductions (31% in operating costs and 25% in R&D), with no significant evidence of the development of new AI-based applications. In this profile, technology is used mainly as a supporting tool, rather than a driver for strategic transformation.

Table 5. Perceived benefits of AI adoption, by adopter profile (in percentages)

BENEFIT	DEVELOPERS	INTEGRATORS	EXPERIMENTERS
Development of new applications that include AI solutions	75%	49%	0%
Development of new non-digital products	9%	10%	19%
Development of new non-digital processes	13%	14%	0%
Increased sales	34%	22%	0%
Reduced R&D costs	38%	37%	13%
Reduced operating costs	38%	58%	31%
Improved market share	28%	15%	13%
Access to new markets	31%	10%	19%
Access to new investments	6%	5%	13%
No changes observed	0%	3%	6%
I don't know	3%	0%	6%

These findings suggest a clear conclusion: AI generates value, but not automatically. The greatest returns are seen where internal capabilities, technological strategy, and leadership exist to integrate AI into the core of the business model. Without these elements, adoption tends to produce limited, efficiency-focused benefits, without translating into innovation, scalability, or a sustainable competitive advantage. In this sense, the gap is not only in terms of technology access, but also in terms of the capacity to transform it into actual economic growth.

4.10 Governance and risk: responsible AI management evolves alongside technological maturity

The study findings show a direct relationship between the degree of AI adoption and the startup's ability to manage risks. While the most advanced companies have begun to institutionalize governance practices, most AI integrators and experimenters still operate with nascent or nonexistent frameworks.

- AI developer startups exhibit the highest levels of maturity in risk management. Within this group, 50% report having internal policies for the responsible use of AI, and 31% state that they have structured processes in place for identifying and mitigating risks. Furthermore, the contractual dimension emerges as a key governance mechanism: half of these startups report that their clients include compliance requirements in their contracts, and 25% report actively complying with local or international regulations. To a lesser extent, they also receive guidance from investors (16%) or resort to third parties to ensure ethical or legal compliance (25%).

- AI integrator startups exhibit a more heterogeneous and fragmented pattern. Only 27% have basic internal policies and 17% have structured risk management processes in place, while more than 30% admit they do not apply any specific measures. In this profile, governance appears as reactive and reliant on external actors: contractual requirements with clients (15%) and third-party support (24%) often compensate for the lack of consolidated internal frameworks.

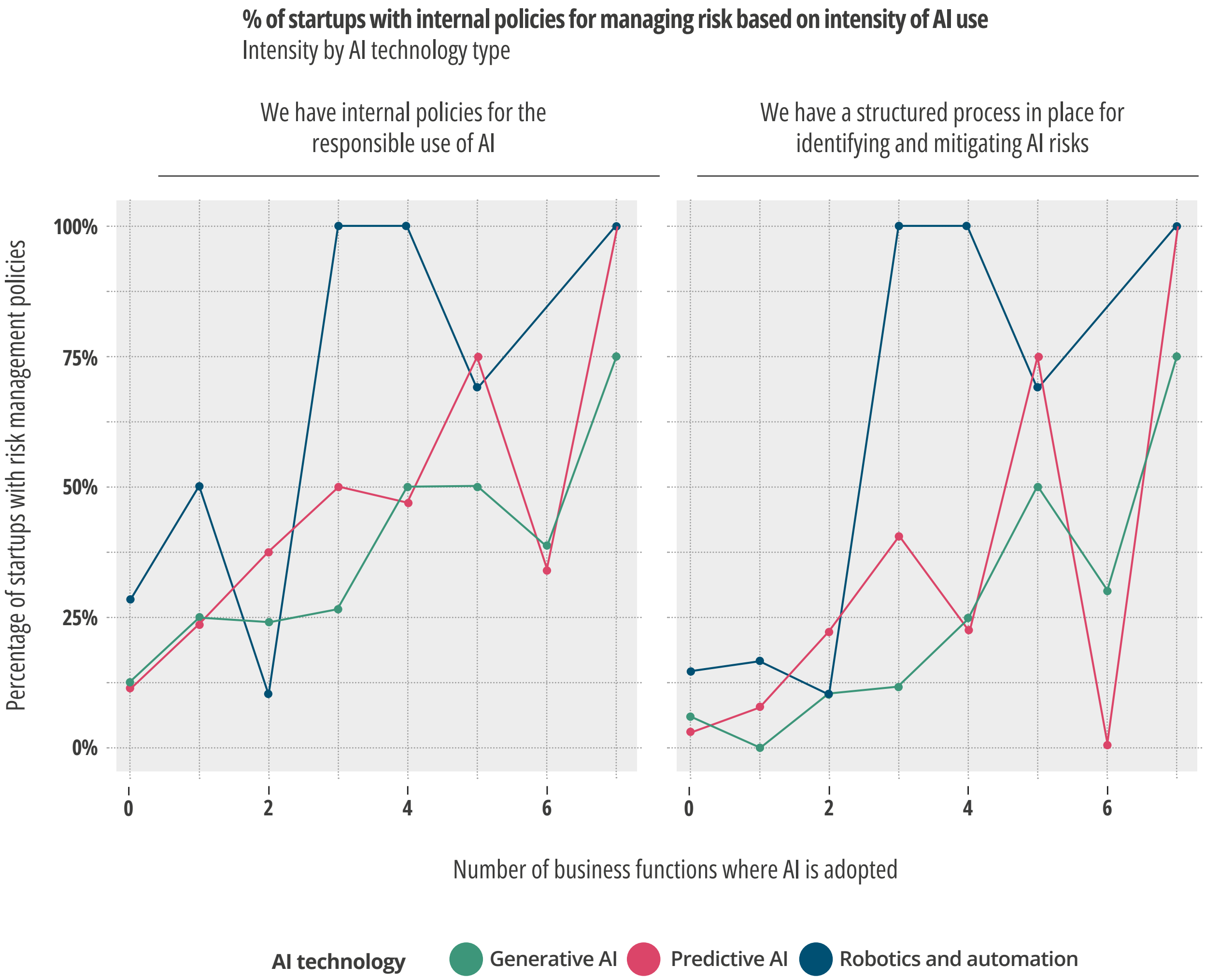
- AI experimenter startups exhibit the most critical scenario. The majority (56%) does not implement any specific measures to manage risks associated with AI use. Only 13% state that they have basic internal policies, and none report having structured processes, active regulatory compliance, or investor support. In this group, AI adoption occurs virtually without formal governance.

Table 6. Risk management efforts in AI adoption (in percentages)

RISK MANAGEMENT	DEVELOPERS	INTEGRATORS	EXPERIMENTERS
We have internal policies in place for the responsible use of AI.	50%	27%	13%
We have a structured process in place for identifying and mitigating AI risks.	31%	17%	0%
We comply with local regulations and/or those of the countries where we are selling our products.	25%	17%	0%
Our investors guide us on minimum requirements (included in the term sheet) and/or guide us on how to carry out responsible and safe adoption of AI.	16%	2%	0%
Compliance issues arise in contracts with clients.	50%	15%	13%
We rely on third parties to ensure ethical or legal compliance.	25%	24%	0%
We do not apply any specific measures.	6%	31%	56%

A common finding is that risk management is closely linked to the intensity of AI use. As startups use AI across more business functions, they are more likely to have internal policies and structured mitigation processes in place (Figure 7). In other words, governance does not precede adoption but rather emerges as a result of its increasing operational prominence.

Figure 7. Risk management policies according to intensity of AI use



This pattern reveals a structural tension: AI is being deployed faster than the governance capacity to manage it responsibly. The institutionalization of risky practices depends not only on the regulatory framework, but also on the organizational maturity, leadership, and pressure from clients, markets, and investors. Without clear ethical, legal, and operational management mechanisms, AI adoption risks creating reputational, regulatory, and trust-related vulnerabilities that can limit its scalability and long-term sustainability.

4.11 Access to capital, data privacy and security, and shortage of solutions as the main barriers to AI scaling.

AI adoption among startups in LAC faces barriers that go beyond technological availability. Among the most relevant, three obstacles appear consistently: lack of adequate funding, concerns about data privacy and security, and scarcity of AI solutions tailored to the needs of businesses (Figure 8).

- **Among developers, the most advanced startups in terms of AI adoption, the main obstacle is access to specialized capital:** 72% identify lack of funding as a critical hurdle, followed by data privacy and security (55%) and shortage of investors with AI expertise (54%). In this group, barriers are associated with the need for accessing patient capital, capable of understanding technological risks and supporting R&D-intensive processes.
- **Integrator startups face a more balanced pattern of barriers.** The main barrier is data management (66%), followed by lack of funding (59%), difficulties in training talent (57%), and uncertainty about return on investment (ROI), (56%). Here, the challenges combine constraints in internal capabilities with doubts about the economic value of adoption.
- **In the case of experimenter startups, barriers are more structural: 83% cite the shortage of providers capable of offering tailored solutions as the main obstacle,** followed by lack of funding (82%) and privacy and security concerns (66%). In this profile, adoption is hindered both by their limited access to technology and their low in-house capacity to implement AI.

Figure 8. Obstacles faced by LAC startups in AI adoption, by adoption profile

	DEVELOPERS				INTEGRATORS				EXPERIMENTERS			
	Low	Medium low	Medium high	High	Low	Medium low	Medium high	High	Low	Medium low	Medium high	High
Staff reluctance	50	17.9	14.3	17.9	26.4	35.8	26.4	11.3	66.7	16.7	8.3	8.3
Suppliers with suitable solutions	34.5	34.5	24.1	6.9	33.3	24.1	33.3	9.3	16.7	0	50	33.3
Data privacy and security	13.8	31	27.6	27.6	12.5	21.4	39.3	26.8	16.7	16.7	33.3	33.3
Adequate financing instruments	13.8	13.8	31	41.4	18.2	21.8	25.5	34.5	8.3	8.3	41.7	41.7
Legal uncertainty	24.1	34.5	24.1	17.2	24.1	40.7	16.7	18.5	25	25	25	25
Estimating ROI	20.7	34.5	24.1	20.7	27.8	14.8	31.5	25.9	33.3	25	33.3	8.3
Investors' acceptance	10.3	34.5	20.7	34.5	21.8	27.3	36.4	14.5	41.7	8.3	41.7	8.3
Secure cloud computing	48.3	20.7	20.7	10.3	40.7	29.6	22.2	7.4	16.7	33.3	41.7	8.3
Staff training	28.6	21.4	42.9	7.1	14.8	27.8	44.4	13	25	58.3	8.3	8.3

Percentage (%) of mentions by profile: 0 20 40 60

Overall, results reveal a gradient of obstacles along adoption pathways. While AI developer startups face financial market failures, integrators grapple with capacity and ROI constraints, and experimenters struggle with basic shortcomings in supply and technological support. The main barriers to AI in the region are not technical, but systemic. Overcoming them requires strengthening not only technology, but also the ecosystem that makes it viable: funding, talent, suppliers, data reliability, and governance.

4.12 Policies for supporting AI adoption: information on use cases as the main need identified by startups.

The study findings evidence that the main enabler of AI adoption for startups in LAC is the availability of practical and validated information on real-world use cases in the industry. In an environment of high technological uncertainty, companies seek concrete examples that will help them to understand where, how, and with what impact AI can be applied to their business models.

This need is cross-cutting to all adoption profiles: 66% of developer startups, 63% of integrator startups, and 56% of experimenter startups rate information on use cases as highly relevant for guiding their technology decisions. At a sector level, demand is especially high in sectors such as health, services, and agriculture and natural capital, where applicability of AI depends heavily on context and empirical validation. Beyond the need for information on use cases, additional distinct priorities emerge.

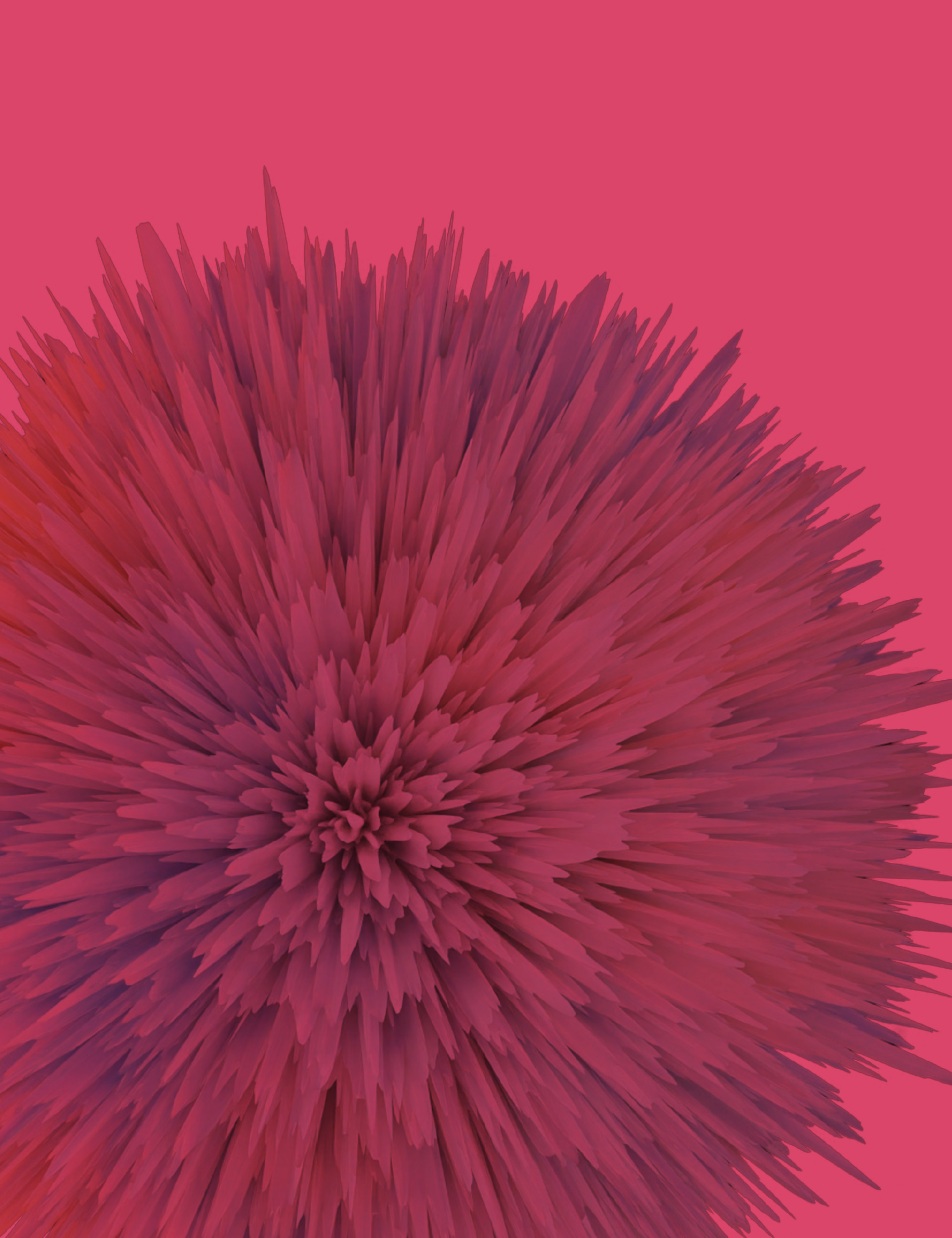
Integrator startups demand information on ROI (49%), reliable suppliers (39%), and regulations (34%), thus reflecting the need to reduce both economic and operational risks. Developer startups also prioritize regulatory knowledge (56%), along with return rates (50%), certifications (41%), and access to specialized suppliers (41%), evidencing concerns about scaling in complex and regulated environments. Experimenter startups, on the other hand, focus their interest on identifying reliable suppliers (50%) as a first step for initiating their adoption processes.

Overall, results suggest a paradigm shift in support policies: startups are demanding fewer direct financial incentives and more knowledge infrastructure. To accelerate the responsible and scalable adoption of AI, public policies should prioritize the dissemination of successful experiences, accreditation of providers, development of standards, and provision of clear information on regulatory frameworks. In emerging economies, applied knowledge emerges as the primary asset for transforming technology into real impact.

Figure 9. Needs for supporting AI adoption, by adoption profile

	DEVELOPERS	INTEGRATORS	EXPERIMENTERS
Information on expected ROI rates	4	3.9	3
Information on current and future data and AI regulations	3.9	3.5	3.2
Information on trusted AI solution providers	3.3	3.4	4
Information on reliable private advisory services and sources of information	3.2	3.6	3.7
Information on use cases in the industry	4.2	4.2	4.2
Certifications or accreditation systems for AI solution providers	3.5	3	3.1

Average values (0 =Irrelevant, 5= Very relevant): Average values (0 =Irrelevant, 5= Very relevant)



V.

FEATURED CASES OF AI ADOPTION IN LAC

CASE AINWATER
(Chile, founded in 2021)

A developer of predictive AI for optimizing water treatment plants.

Ainwater was created as a result of a recurring operational problem observed in water treatment plants: sensors and large volumes of data are available, but they are rarely used systematically for decision-making. Most plants —both industrial and municipal— operate with legacy systems, spreadsheets, and manual adjustments based on operators' experience. Thus, the opportunity was clear: underutilized data could be transformed into operational intelligence.

From its inception, Ainwater was positioned as a developer of industrial AI. Its approach combines process engineering, plant digitalization, and machine learning for building predictive models that can anticipate deviations and recommend specific operational adjustments (aeration, dosage, pH, blower use). The business model is B2B, with ongoing operating contracts in the food, beverage, and utilities industries in Chile, Uruguay, Mexico, and Brazil.

AI was incorporated in the company as the core of its R&D. Each implementation begins with intensive digitalization work: connecting sensors, purging incomplete historical data series, and rebuilding the plant's actual behavior. Based on this, Ainwater trains a specific model for each plant, since operating patterns are not generalizable across facilities. Models combine traditional machine learning techniques (random forest, XGBoost, time series models) with calibrations based on knowledge of hydraulic, chemical, and biological processes.

The platform not only predicts but also delivers actionable operational recommendations. In a sector where aeration accounts for approximately 40% of operating costs, this capability has a direct impact on efficiency. Recently, the company began exploring GenIA as an operational assistant for interpreting complex trends, although this is not the core of the product.

The adoption of AI has generated tangible benefits: reductions of between 10% to 15% in energy use within a few weeks, anticipation of failures before regulatory non-compliance events, and increased operational stability. At a strategic level, Ainwater's technical robustness enabled commercial scaling and the development of a hard-to-replicate algorithm asset built on real, structured data from industrial processes.

Ainwater's case offers some clear lessons:

1. Predictive AI only works where reliable physical data exist; without sensors and continuous data, predicting is not feasible.

2. Process digitalization is a prerequisite, rather than an additional element: most efforts focus on organizing data before modeling.

3. Industrial AI requires the combination of data science and process engineering; without process understanding, models lose their operational value.

CASE GUSKA
(Uruguay, founded in 2024)

A developer startup adopting AI to accelerate the design of new cancer therapies.

Guska is a Uruguayan biotechnology startup that emerged from the scientific work developed at the Pasteur Institute in Montevideo and the University of the Republic of Uruguay. The venture was founded with the purpose of developing synthetic RNA oncolytic viruses capable of safely attacking tumors without harming healthy cells in the process.

AI was incorporated in Guska through its critical R&D function. The team faced the classic bottleneck: each viral candidate requires years of experimental design, multiple validation cycles, and high costs. The key question was: how can the startup scale this process without multiplying resources? Thus, Guska decided to build a GenAI predictive platform capable of designing viruses based on clinical requirements. This required creating a data foundation based on multiple data sources (proprietary experimental results, patented technologies, scientific publications and open databases) as input for the development of a hybrid platform that uses GenIA to design synthetic viral genomes, and applies predictive AI to prioritize candidates based on efficacy and safety.

Since the company lacked both specialized talent and the financial capacity to hire it to pursue its technology strategy, it opted to build a strategic alliance with Marvik, a leading AI company in Uruguay. Marvik's team is working alongside Guska's scientific team on the development of the generative minimum viable product (MVP). The platform operates through a secure, closed pipeline: design > computational prioritization > external synthesis > experimental validation at the Pasteur Institute in Montevideo.

The incorporation of AI has transformed Guska's research process by expanding the viral design pipeline and reducing the trial-and-error cycle, as predictive models prioritize the most promising candidates prior to synthesis. This decreases the number of experiments required and optimizes Guska's resources.

Guska's experience offers several lessons for startups seeking to integrate AI into their scientific or technological processes.

1. Guska understood that AI could amplify its biological discovery process. The key to success lies in relying on expert knowledge, proprietary data, and sound biological rules. The quality of initial input data will determine the potential of AI.

2. In the early stages, hiring in-house staff is not always the best strategy. Partnering with expert teams allow firms to move faster, build capacity, and mitigate risks.

3. AI adoption requires specific governance structures, especially when applied to sensitive domains such as biology. Defining guardrails, permissions, human oversight, and early validation processes avoids ethical and reputational risks.

CASE INTELIMED.AI
(Chile, founded in 2011)

An AI integrator startup that applies regulated AI (software as a medical device) to support clinical diagnosis and automate regulatory and operational processes in healthcare.

Intelimed.AI was born as a result of an observation: Latin American hospitals face an oversupply of AI solutions in healthcare, but lack the technical and regulatory criteria to distinguish between models with clinical evidence and commercial tools without validation. “AI in healthcare is full of information and misinformation”, states its founder. Faced with this problem, Intelimed anchored its positioning, not as an algorithm developer, but as an integrator specializing in regulated clinical AI.

Its proposition involves selecting, comparing, validating, and implementing AI models certified as Software as a Medical Device (SaMD), acting as a technical and regulatory bridge between international AI providers and local healthcare systems. Intelimed supports hospitals and clinics in risk assessment, reviewing scientific evidence, tailoring to clinical workflows, and complying with international regulatory frameworks. Its business model combines technological integration, regulatory services, and clinical support, with a strong educational component geared towards medical teams and management.

Intelimed's adoption of AI operates on two levels. The first is product-oriented, aiming at integrating regulated clinical models developed by third parties. This process includes comparative analyses between solutions, internal validations, performance testing with local data, and generating documentation for regulatory compliance. The company emphasizes that this layer is critical, since many institutions lack in-house capabilities to assess the true quality of an algorithm beyond marketing considerations.

The second level is the use of GenIA developed in-house. Intelimed developed Intelimed Brain, a tool that automates regulatory documentation, synthesizes scientific evidence, contextualizes regulations, and produces standardized comparisons between models. In a sector with intensive technical reports and formal requirements, this tool reduces processing times and improves work consistency. GenIA is also used for internal organization, educational materials, communication, and support for R&D processes. In a small organization, this automation is key for scaling capabilities.

Results are visible both to clients and internally. In the case of hospitals, Intelimed reduces the uncertainty associated with adopting diagnostics AI, thus facilitating evidence-based decisions and the responsible use of regulated technologies. In the case of Intelimed, GenIA has enabled the reduction of operating and R&D costs, improved team efficiency, strengthened its competitive positioning, and allowed access to new markets and investments. The company has also developed new non-digital practices, such as designing safer clinical workflows and AI-supported medical training processes.

Intelimed's case offers some clear lessons:

1.In healthcare, AI adoption depends on rigorous validation, clinical evidence and regulatory compliance.

2. Misinformation is a structural obstacle; educating clinical teams is as important as integrating technology.

3. GenIA can transform regulatory and document-related processes, but it does not replace clinical judgment nor formal standards.

4. Thorough knowledge of the regulatory framework becomes a key competitive differentiator for AI integrator startups.

CASE KILIMO
(Argentina, founded in 2014)

An AI developer startup that applies predictive and generative AI to optimize water use in agriculture.

Kilimo was created as a result of a specific concern: in irrigated agriculture, one of the region's heaviest water-intensive activities, decisions about when and how much to irrigate continued to rely on intuition and rules of thumb, even in contexts of increasing water scarcity and climate variability. The company's founding team, made up of agronomists and data specialists, identified a clear gap between the wealth of available information and its effective use for decision-making.

After an initial phase that combined sensors and climate data, the company adopted a more scalable approach based on satellite data, historical climate information, and proprietary models capable of estimating water demand without the need for on-site equipment. This decision proved strategic: it reduced adoption barriers and allowed the company to operate in heterogeneous productive contexts. Over time, Kilimo further expanded to several Latin American countries and the United States, consolidating its status as a leading voice in climate-smart agriculture. The company's business model combines B2B subscriptions and technical support services, aimed at optimizing irrigation, measuring savings, and generating verifiable reports on efficient water use.

Kilimo's adoption of AI unfolded in two stages. The first stage, which was product oriented, focused on predictive models that integrate climate, soil, satellite images, and farm-level historical data to estimate water demand. This AI approach proved critical for capturing the huge variability between crops, regions, and cropping seasons, and for scaling the solution across multiple geographical areas lacking homogeneous infrastructure. The second stage, initiated in 2023, marked a shift towards GenAI applied to internal processes. Adoption was mainly bottom-up: support, sales, marketing, and training teams began using AI to summarize technical information, write reports, organize databases, and document processes. In a regional organization that had grown organically, AI became a tool for systematization and coordination.

Results are visible on two levels: at a productive level, predictive AI improved the accuracy of irrigation recommendations and allowed to generate measurable and validated water savings, further enabling new services linked to verifiable measurements and water credits; at an organizational level, GenIA accelerated repetitive tasks, streamlined informal processes, and freed up capacity for strategic functions, thus strengthening the quality and consistency of internal work.

The Kilimo case offers some clear lessons:

1. Predictive AI is more robust when it is fed with diverse, contextualized data accumulated over time.

2. GenIA can be a powerful driver for internal organization, prompting firms to document and standardize processes that were previously implicit.

3. AI adoption in organizations does not happen automatically: it requires culture, support, and room for experimenting.

4. In agriculture, algorithmic sophistication must be balanced with practical applicability; models need to be accurate, while assuring usability by producers with heterogeneous capabilities.

5. Rather than replacing it, AI leverages agronomic knowledge. Human interpretation remains key in complex and changing production systems.

CASE SUNNYBOTICS

(Colombia, founded in 2021)

An AI integrator startup that applies robotics to automate solar panel maintenance, driven by strong university links.

Sunnybiotics was created in the city of Neiva (Colombia), as the result of an operational diagnosis: the solar industry was growing rapidly, but plant maintenance was still manually-operated, expensive, and risky. Cleaning and inspecting solar panels on a daily basis require covering large areas, facing harsh environmental conditions, and taking significant operational risks. Therefore, Sunnybiotic's founders, who are engineers graduated from the University of Pamplona, identified an opportunity for process automation through the use of robotics and artificial intelligence.

The first development was a modular robot, created in the university premises, capable of moving across panels. However, the key realization was that its value resided not only in the hardware used, but in providing it with robotic AI to interpret the environment and generate useful information. As one of the founders pointed out: "The robot had to see, understand, and tell us what was happening". From this initial need, Sunnybiotics further evolved into an AI integrator startup by incorporating AI applied to field robotics.

AI was incorporated at the product core at two levels. Firstly, in the robot's autonomy: computer vision and navigation models enable it to recognize panels, detect dirt, shadows, and obstacles, modify its trajectory, and operate in uneven environments. Robots integrate environmental sensors (for moisture, temperature, radiation) that feed into a proprietary database, which is further used to characterize soiling and anticipate efficiency losses. Some of these developments were carried out in collaboration with professors and students from the University of Pamplona, thus consolidating a strong university-industry link.

Secondly, Sunnybiotics implemented GenIA to automate internal processes. The generation of contracts, technical reports, and commercial communications shifted from being manually-operated to becoming partially automated, thus reducing processing times and freeing up organizational capacity within a small team.

The adoption of AI allowed to transform a manual service into a scalable, data-driven solution. The robot operates with greater autonomy, reducing labor costs and risks for operators. At the same time, the company created a new digital product: automated reports with heat maps, dirt indicators and maintenance recommendations, all of which were non-existent in the traditional system. Also, GenAI contributed to streamline internal administrative processes and improve operational efficiency.

The Sunnybiotics case offers some relevant lessons:

1. Robotic AI requires the use of data specific to the physical environment, which can only be obtained through intensive operations and trial and error cycles.

2. University collaboration can be a decisive enabler for applied innovation.

3. In infrastructure sectors, commercial adoption is usually slower than technical adoption, requiring pilot projects, field validation, and customer support.

4. GenIA can strengthen non-technical functions — such as contracts, reports and management — whenever startups face restrictions at an organizational scale.

CASO YEDA HEALTH
(Uruguay, founded in 2023)

A startup specializing in customized health that incorporated AI to better understand each body's unique response.

Yeda Health is a Uruguayan digital health startup that was developed based on key scientific evidence: people with similar characteristics can exhibit very different metabolic responses to the same foods. This finding —documented through longitudinal studies using glucose sensors and nutritional records— led to a critical conclusion: nutrition should be customized, and AI is the tool to make it scalable.

The company began as an AI developer startup, with a team of founders that combines expertise in biotechnology, biomedical engineering, and AI. Its business model is B2B2C: the platform is deployed across clinics and health centers (nutrition, endocrinology, fitness, and longevity), which further make it available to their patients. The product combines a user app (glucose sensors and food logging), a dashboard for professionals, and AI models that generate customized metabolic health recommendations.

AI was incorporated in Yeda Health as its product core. Its technical approach is distinctive: instead of training a population-wide model, the company builds a machine-learning model for each individual, which has been previously trained by using the data generated by each user. The system integrates continuous data on glucose levels, meal logs (processed with computer vision and multimodal models), sleep patterns, physical activity, and body composition. From said data, models learn individual metabolic patterns and can predict glycemic responses in real time, even when the underlying biological mechanisms are not yet fully understood.

Initially, Yeda attempted to develop computer vision models in-house for food recognition, but the associated costs and data requirements proved prohibitive. The availability of third-party multimodal models allowed Yeda to incorporate this feature through APIs, thus reducing time and costs without losing control of the algorithmic core. The AI layer and data architecture are developed in-house, while the software and app are outsourced under a staff augmentation approach.

The adoption of AI enabled the creation of a product that would otherwise not exist without machine learning: metabolic recommendations with greater accuracy than traditional metrics, scalability of learning as new users are incorporated and more features are added based on intelligent automation. Clinical validation, through a pilot program at the Albert Einstein Hospital (Brazil), demanded high standards of privacy, security and governance, thus strengthening the system's reliability.

Yeda Health's experience offers several relevant lessons:

1. Deep customization in health requires proprietary, continuous, and multimodal data; without them, AI will not add differential value.

2. In sensitive domains, the legitimacy of AI depends on clinical validation and robust governance frameworks.

3. Integrating external AI can accelerate development, provided the scientific and algorithmic core remains under control.

4. Engaging healthcare professionals is key to reducing risks and ensuring responsible use of AI.

VI.

RECOMMENDATIONS FOR STRENGTHENING RESPONSIBLE AI ADOPTION IN LAC STARTUPS

The study findings show that AI adoption among startups in LAC depends not only on access to technology, but also on a broader set of organizational capabilities, environmental conditions, and institutional frameworks. The differences between AI developer, integrator, and experimenter startups evidence that AI consolidates when there is a combination of specialized talent, high-quality data, strategic leadership, and effective governance.

Based on this, five priority lines of action are identified so that the IDB, venture capital funds and governments in the region can promote an AI adoption approach that is not only broader, but also safer, more responsible and inclusive.

1. Developing foundational capabilities in startups from early stages

The study shows that those startups that are most advanced on AI use possess three critical assets: hybrid talent (technology + sector), data infrastructure, and technical leadership. In contrast, experimenter startups lack even the minimum capabilities to identify, structure, and scale use cases.

This suggests that support policies should prioritize the development of foundational capabilities, rather than simply providing tools.

AI readiness programs aimed at early stage startups —focused on data diagnostics, structuring of internal processes, and strategically defining use cases— can significantly reduce barriers to entry. This should be complemented with tools for developing hybrid talent, through specialized bootcamps and technical residencies at universities, as well as some degree of financial support for building initial AI architectures (data pipelines, cloud infrastructure, and preliminary models).

These actions are especially relevant in sectors such as health, agriculture and infrastructure, where adoption is still in its infancy and local customization is essential.

2. Scaling adoption through financial instruments specialized in AI

The lack of adequate funding emerges as the main cross-cutting obstacle. Startups that either develop or integrate AI require resources not only to grow, but also to experiment, validate, and adapt models to real-world contexts.

In this framework, the recommendation is to move towards specific financing instruments for applied AI: co-financing funds for pilot testing in real-life environments (hospitals, industrial facilities, agriculture, fintech), support lines for R&D in model customization and IDB-VC co-investment approaches aimed at startups with high technological potential and social impact.

Rather than providing funding for "digital startups", these instruments should explicitly assess technological maturity, data quality, relevance of the use case, and risk management capacity.

3. Repositioning investors as strategic stakeholders for responsible adoption

Among the most critical findings of the study is the marginal role that investors play today in AI governance: less than 10% introduce AI criteria in their investment processes or term sheets.

There is a clear opportunity to transform VCs and angel investors into active agents for responsible adoption by incorporating AI due diligence tools that assess data quality, vendor reliance, and ethical and regulatory risks. This is coupled with the need to train investors in technology evaluation, promote the inclusion of responsible AI clauses in investment contracts, and engage accelerators in technical and regulatory mentoring programs.

AI should not only be a growth factor, but also a key element of risk governance within venture capital.

4. Strengthening regulatory frameworks and governance capacities

The significant lack of regulatory awareness —63% of startups do not know if AI is regulated in their country— reveals a substantial institutional gap. At the same time, only developer startups exhibit systematic risk management practices.

This suggests the need to build a soft governance infrastructure, through practical guidelines for responsible AI tailored to startups, national ethical-regulatory support nodes, and light and gradual certification schemes that do not operate as entry barriers, but rather as minimum standards.

Likewise, when regional observatories that assess the impact and safety of AI articulate their work with universities, they can contribute to the generation of evidence, collective learning, and institutional legitimacy.

5. Building a regional enabling environment for AI innovation

Finally, the study shows that most startups need to customize models to their local context in terms of language, climate, biology, production practices, and regulations. This implies that, rather than being a consumer of global solutions, the region needs to develop its own AI innovation capabilities.

Priority actions include the creation of high-quality regional open data platforms (climate, health, environment, infrastructure), the promotion of interoperability standards to facilitate regional scalability, systematic dissemination of Latin American use cases (a demand reported by around 60% of startups) and strengthening university-industry-startup partnerships.

Hence, living labs, technology hubs and real-world testing environments —hospitals, industrial plants, agricultural systems— are emerging as key spaces to bridge the gap between technological development and productive adoption.

Overall, recommendations underscore the same principle: AI adoption in startups is not a technological problem, but a systemic challenge. It requires talent, data, financing, regulations, organizational culture, and collaborative ecosystems.

In the case of LAC, AI represents a strategic opportunity for closing structural gaps in productivity, competitiveness, and inclusion. However, its impact will depend on the ability to build an environment where innovation is not only fast, but also responsible, contextualized, and aimed at sustainable development.

REFERENCES

Calvino, F., Samek, L., Squicciarini, M., & Morris, C. (2022). Identifying and characterizing AI adopters: A novel approach based on big data, OECD Science, Technology and Industry Working Papers 2022/06.

Chalmers, D., MacKenzie, N.G., & Carter, S. (2021). Artificial intelligence and entrepreneurship: Implications for venture creation in the fourth industrial revolution. Entrepreneurship Theory and Practice, 45(5), 1028-1053.

Herrera Giraldo, M., Gallego Acevedo, J.M., Gutiérrez Ramírez, L.H., Vargas, F. and Pereira, M. (2024). The Diffusion of Artificial Intelligence in an Emerging Economy. Evidence at the Firm Level in Colombia, IDB.

McCarthy, J., M.L. Minsky, N. Rochester, and C.E. Shannon. 1955. A proposal for the Dartmouth summer research project on artificial intelligence. http://www-formal.stanford.edu/jmc/history/dartmouth/dartmouth.html

McElheran, K., et al. 2024. AI Adoption in America: Who, What, and Where. Journal Of Economics & Management Strategy, 33 (2), 375 – 415. https://doi.org/10.1111/jems.12576

McKinsey (2025). The State of AI. How organizations are rewriting to capture value. https://www.mckinsey.com/~/media/mckinsey/business%20functions/quantumblack/our%20insights/the%20state%20of%20ai/2025/the-state-of-ai-how-organizations-are-rewiring-to-capture-value_final.pdf

OECD (2024). "Explanatory memorandum on the updated OECD definition of an AI system", OECD Artificial Intelligence Papers, No. 8, OECD Publishing, Paris, https://doi.org/10.1787/623da898-en.

OECD/BCG/INSEAD (2025). The Adoption of Artificial Intelligence in Firms: New Evidence for Policymaking, OECD Publishing, Paris, https://doi.org/10.1787/f9ef33c3-en.

APPENDIX A - SURVEY METHODOLOGY

For the purpose of approximating the universe of AI-adopting startups in LAC, the Crunchbase proprietary repository was selected as the primary source for identifying, collecting and classifying startups in the region.

Methodological criteria for identifying the unit of analysis:

1. Use of the Crunchbase database to identify: active LATAM startups adopting AI (non-AI-native)

- Geographic location: 'Headquarters Location' in 'Latin America'
- Last round of funding:

  - *'Last Funding Date' within the past 4 years*

  - *'Last Funding Type' limited to: 'pre-seed', 'seed', 'Series A, B, C and D' and 'Convertible Note'*
- Industries: 'Industry Groups' excluding 'Artificial Intelligence' (AI)

2. Identification of specific focus based on IDB Lab's Impact Challenges (see Table A.1.) .

- In Crunchbase, the filter was applied by industry sector, equivalent to the the matic verticals in Table A.1. (e.g., 'health').

- Based on website and LinkedIn URLs provided by the Crunchbase download, the horizontal (IC) filter was applied, according to the procedure detailed in the corresponding box.

(3) Advanced Search section for companies: https://www.crunchbase.com/discover/organization.companies

Table A.1. Impact Challenges (IC) defined by IDB Lab for the period 2025-2027

	IMPACT CHALLENGES	ILLUSTRATIVE SOLUTIONS	ALIGNMENT WITH THEMATIC VERTICALS				
			Health	Talent & Employment	Essential Infra. Services	Agriculture & Natural C	Financial Inclusion
IC1	**Improve healthcare access and quality for patients with non-communicable diseases (NCDs), especially those facing barriers**	Telehealth, direct-to-conser (D2C) care, AI and health analytics, accessible insurance, low-cost health benefits and drug delivery.	✓				
IC2	**Strengthen healthcare by addressing workforce shortages, prioritizing rural areas**	Tech-enabled healthcare training and upskilling, community healthcare models.	✓	✓			
IC3	**Bridge the skill gap and expand job opportunities for underprivileged and diverse populations**	Tech-enabled upskilling and reskilling, remedial school, workforce, cognitive, technical, and social skills, close digital gap for self-employed and diverse workers.		✓			
IC4	**Improve access to affordable, efficient, and high-quality water and sanitation services and clean energy**	W&S efficiency solutions, digitalization of service providers, govtech, nature-based solutions, clean-energy solutions.			✓		
IC5	**Accelerate the energy transition and the adoption of green transportation solutions in urban areas**	New and clean transportation technologies, digitalization of service providers, energy efficiency and clean energy, outcomes-based finance.			✓		
IC6	**Drive the green transition for small agricultural producers and firms**	Efficient and climate resilient agricultural models (adaptation and mitigation), agtech, nature-based solutions.				✓	
IC7	**Boost the availability and access to nutritious food for stronger food security**	Precision agriculture, traceability systems, biotech, midstream tech, food production and delivery, food waste mitigation, nature-based solutions.				✓	
IC8	**Expand financial access to underserved segments**	Tailored digital financial products and services such as asset loans, health and unemployment insurance, digital payments and tokens, retirement and savings for informal and independent workers.					✓

	IMPACT CHALLENGES	ILLUSTRATIVE SOLUTIONS	ALIGNMENT WITH THEMATIC VERTICALS				
			Health	Talent & Employment	Essential Infra. Services	Agriculture & Natural C	Financial Inclusion
IC9	**Bridge the financing gap for small businesses prioritizing IDB Lab's thematic verticals**	Digital financial products and services for small businesses, tokenization, new technologies and risk assessment models for financial intermediaries.	✓	✓	✓	✓	✓
IC10	**Unlock the silver economy by empowering older people**	Tech-enabled reskilling, tailored financing products, tailored healthcare, high quality care services, inclusive infrastructure, access to jobs.	✓	✓	✓		✓
In all these challenges IDB Lab addresses transversally climate risks and social gaps.							

Box 1 - Procedure used for identifying the universe of startups from Impact Challenges

The energy industrial sector was selected as a pilot for data extraction and optimization due to its smaller number of startups. The first thematic download with structured fields was generated from this segment.

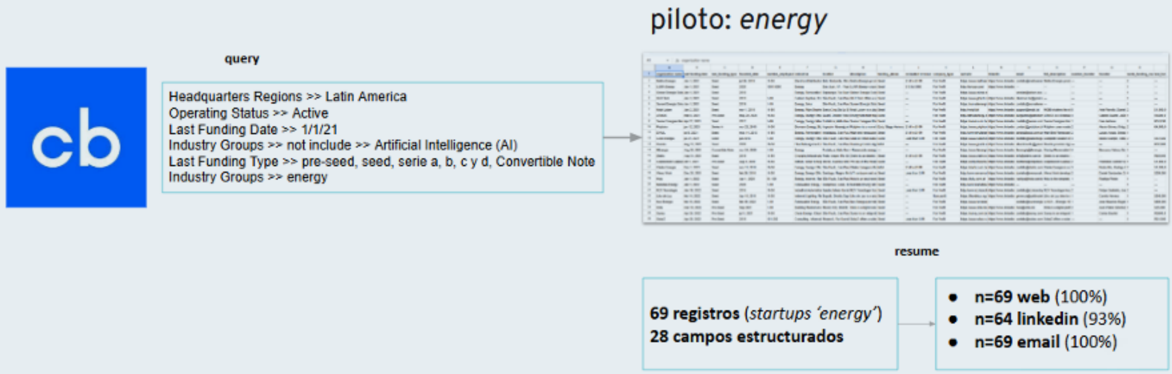


Image 1. Diagram - First Level Extraction Process

The goal of this initial download was to systematically obtain the website URLs and LinkedIn profiles of pre-selected startups. In addition, 28 supplementary fields were collected for further analysis. Upon completion of this stage, a high retrieval rate was achieved: 100% for website URLs, 93% for LinkedIn URLs, and 100% for emails.

These findings allowed us to move on to the identification and classification phase according to impact horizontals defined by the IDB.

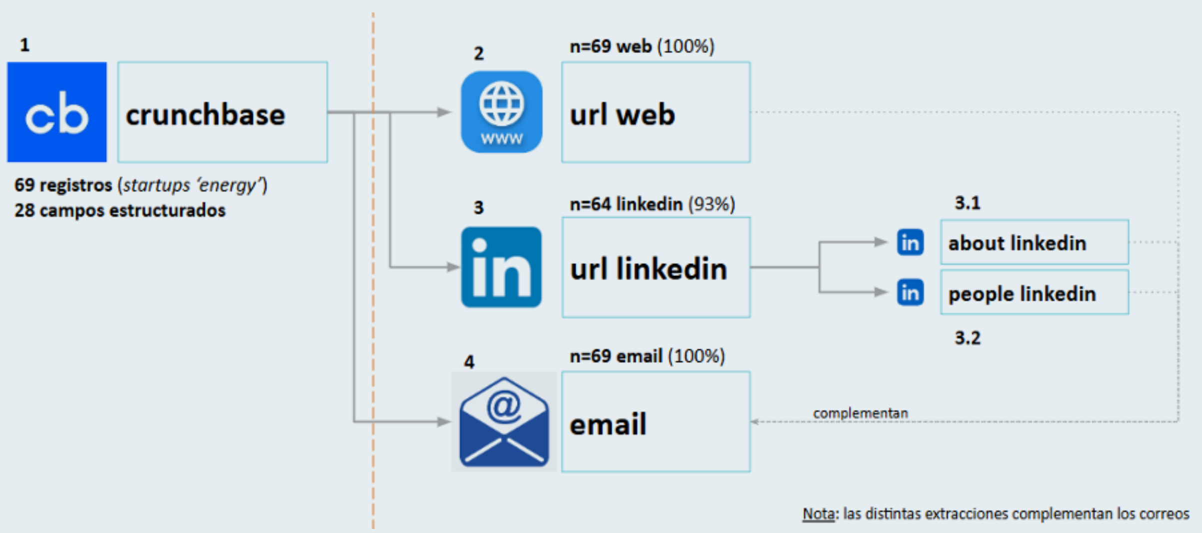


Image 2. Diagram - Second Level Extraction Process

Classification tests were conducted using complementary approaches. This included using the original fields provided by Crunchbase (primary download) and information extracted from the 'About' sections on LinkedIn and 'header' and 'body' sections on websites (secondary rounds). A direct visit approach using structured URLs was also evaluated, allowing navigation to a second nesting level for analysis and classification.

Regarding the techniques applied, methods based on bags-of-words identification were used , with key labels weighted by impact filter, and context-based approaches using the "Gemini-2.5-flash" ID reasoning model. The latter showed better performance and was selected as the base model for batch classifications.

Each industry group (according to Crunchbase's classification) was selected based on its alignment with the IDB's strategic thematic agenda. For the energy industry group, the corresponding vertical was 'Essential Services and Infrastructure', associated with Impact Challenges IC-4 and IC-5. Each identification round was structured according to the Impact Challenge, given its specificity, while the vertical was predetermined by the industry group.

Although rounds were performed massively via API, each destination address (startup URL) was processed as an independent query, generating a structured output with classification and verification parameters.

The energy sector pilot project proved key for adjusting and consolidating the overall process.

Database obtained and data collected

A universe of 300 non-AI-native startups in LAC (excluding Brazil) was identified, from which 107 responses were obtained, equivalent to a response rate of 35.7% (see Table A.2). This set constitutes the empirical basis for this report. Participating startups belong to 14 countries in LAC (see Figure A.1) and cover a wide variety of AI application sectors, including health, services, financial inclusion, agriculture and natural capital, infrastructure, talent and employment, among others (see Figure A.2).

Table A.1. Sample and universe distribution by Impact Challenge

IMPACT CHALLENGE (IC)	UNIVERSE	SAMPLE	UNIVERSE %	SAMPLE %
IC1	34	18	10,6%	16,8%
IC2	8	3	2,5%	2,8%
IC3	34	29	10,6%	27,1%
IC4	4	4	1,3%	3,7%
IC5	23	8	7,2%	7,5%
IC6	10	8	3,1%	7,5%
IC7	24	16	7,5%	15,0%
IC8	43	16	13,4%	15,0%
IC9	116	3	36,2%	2,8%
IC10	4	2	1,3%	1,9%

In general terms, the sample adequately reflects the diversity of the 10 Impact Challenges, although it shows a marked underrepresentation of IC9, which is the largest among the universe. This distribution allows for a balanced and cross-cutting coverage of the different impact areas, sufficient to identify patterns and contrasts among sectors and startup types. The sample design was analytical, exploratory, and non-inferential, aimed at identifying adoption dynamics, benefits, obstacles, and organizational capabilities amid different national and sectoral contexts. With a 95% confidence level and p=q=0.5, the estimated global margin of error is ±7.5%, a figure deemed adequate for descriptive and comparative surveys.

Figure A.1. – Sample distribution of startups surveyed, by country where they were founded (in quantities)