Optimisation of Administrative Processes Through Artificial Intelligence: Analysis of Adoption and Trust in Peruvian Companies in The Telecommunications Sector

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Abstract:
In the Peruvian business environment, the adoption of Artificial Intelligence is key to optimising processes. However, its implementation faces challenges due to a lack of resources and cultural barriers. This research aims to analyse the relationship between AI adoption and product innovation, security, organisational preparedness, and perceived ease of use. A non-experimental quantitative design with a structural equation model (SEM) was used, collecting data through structured surveys applied to employees in the telecommunications sector. The results show that AI security has a positive and significant effect on AI adoption ($p = 0.000$), while the perceived ability of the employee directly influences perceived ease of use ($p = 0.003$). In turn, AI adoption has a significant impact on product innovation ($p = 0.000$), process innovation ($p = 0.000$), and AI-driven marketing ($p = 0.000$), confirming that technological confidence and skills development drive greater business efficiency and innovation. In conclusion, AI adoption is strengthened when there is rigorous management of AI security and staff capacity building, as it increases utility by promoting innovation. This work seeks to provide evidence from the Peruvian context, focusing on workers' real experiences with AI and how these can guide solutions tailored to the needs of the sector.

Keywords:: AI adoption; organisational readiness; perceived ease of use; AI marketing; process innovation; AI security

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1. Introduction

In the current business context, the adoption of AI is emerging as a requirement for optimising administrative processes by enabling automation, generating insights, and improving staff performance (Mikalef et al., 2023). However, its adoption remains heterogeneous and depends on technological and organisational conditions. The literature synthesises these determinants through acceptance models that connect perceptions of usefulness with organisational readiness and the environment (Roppelt et al., 2025). In emerging markets, recent studies indicate that organisational readiness and security are high indices that increase the likelihood of AI adoption in large companies (Haq & Suki, 2025). At the same time, adoption acts as a mediator that converts these capabilities into improvements in efficiency, innovation, and performance. Within this framework, the article focuses on how, by increasing AI security, organisations choose to adopt this technology, which allows them to optimise their processes, innovate products and boost marketing.

The adoption of AI is explained by its connection to four complementary vectors, such as organisational readiness, which sets the stage for adoption as it requires subjective norms and managerial support, compatibility with strategy, infrastructure and trust, which are components of *readiness* that guide integration decisions (Urbani et al., 2024). Furthermore, readiness is not only technical, but also relies on knowledge management, whose interaction with technology fuels innovation and efficiency, favouring organisational acceptance of AI-based solutions (Olan et al., 2022). In this framework, ease of use is directly linked to adoption and perceived usefulness, which drive intention to use, while trust acts as a mediator that sustains commitment and continued use (Prasad & De, 2024). In this sense, AI process innovation reduces uncertainty and accelerates value, feeding back into adoption (Holmström & Carroll, 2025). Therefore, AI security conditions acceptance and must be incorporated from the design stage of *readiness*.

Other studies have analysed the impact of AI on innovation, focusing on the possibility of increasing productivity, competitive advantages, and business reconfiguration in highly dynamic markets (Abdul Wahab & Radmehr, 2024; Cooper, 2025). Previous work has focused on the developed world and has not begun to address the challenges of resource-scarce environments, leaving a significant gap in the generalisation for the developing world. Taken together, these studies suggest that AI adoption is related to the level of preparedness in terms of technology, digital infrastructure, talent and leadership, with the latter defining organisational levels, which probably mediate between the adoption of practices and the generation of risks, thus explaining the complex factors that favour or limit the use of these tools (Roppelt et al., 2025; ul Haq et al., 2025). However, infrastructure gaps and technical skill shortages persist, limiting sustainable adoption and identifying methodological gaps, a lack of longitudinal analysis, a lack of candidate perspective, and little consideration of the cultural role, which calls for research that incorporates contextual variables and complementary theoretical approaches. On the other

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hand, recent reviews show that AI drives business model innovation and new sources of competitive advantage in different sectors by reconfiguring processes, value propositions, and revenue streams (Jorzik et al., 2024; Roberts & Candi, 2024). Despite this, conceptual evidence and evidence from developed countries predominate, with little longitudinal and comparative analysis in companies in emerging economies. Furthermore, the adoption of AI shows clearer returns and systemic effects. Chain leaders who adopt AI reduce the risk of disruption and improve coordination with suppliers, as company size enhances the benefits of innovation capacity (Arroyabe et al., 2024; Ayinaddis, 2025; Peretz-Andersson et al., 2024).Similarly, these findings come from contexts and samples with mostly cross-sectional designs, which limits their generalisation and leaves open the question of direct measurement of administrative process optimisation.

In Peru, and in general in less developed economies, there is a knowledge gap regarding the integration of organisational readiness, ease of use, process innovation, AI marketing, and security as determinants of AI adoption and its effects on administrative optimisation. Although the literature shows that *AI readiness* enables differ between developed countries, comparative studies remain scarce (Pramanik et al., 2024). In resource-constrained contexts, trust and the risks of AI continue to be bottlenecks that require adapted security frameworks (Shamim et al., 2023). Given the current situation, integrated approaches are needed that articulate the essential variables with the adoption of AI to estimate its impact on operational efficiency, shorter cycle times, costs, and errors (Hradecky et al., 2022).

This study aims to examine the impact of AI adoption on the administrative process of the telecommunications sector in Peru, relating the title to the factors of the model and determining its effect on the indicators of optimisation and continuous improvement. Likewise, it is possible to find evidence of substantial advances in productivity and performance of routine activities (Muehlemann, 2025). Given their strategic role, these companies can benefit business capabilities (Wei et al., 2024). For this reason, this research aims to provide evidence from the Peruvian context, using real experiences of collaborators using AI and formulating solutions in line with the needs of the sector.

This research was conducted with the aim of analysing the processes related to the adoption of AI. To make this possible, key aspects such as perceived ease of use, perceived usefulness, organisational readiness, AI security, product and process innovation, among others, were considered (Haq & Suki, 2025). The importance of this approach lies in the fact that research on AI continues to lack knowledge of developing economies, which has limited the understanding of the use of these technologies (ul Haq et al., 2025). In Peru, there is limited research on the evolution of AI management. Thus, the study followed recommendations that propose not only considering the intention to use AI but also examining its effects through indicators (Mikalef et al., 2023).

This article presents a review of the literature on the telecommunications business sector in Peru, AI adoption practices and their associated variables, and the development of the hypothesis. The second section explains the methodology used to meet the research objectives. The third section presents the results, and the fourth section analyses the study's findings and their implications. The fifth section describes the conclusions, and the last section analyses the study's limitations and directions for future research.

2. Literature review

2.1. The large enterprise sector in Peru

Truly inclusive growth in emerging economies such as Peru's requires closing governance gaps and promoting innovation with a sustainable approach (Correa-Mejía et al., 2024). In this context, telecommunications companies play a decisive role, as their scale allows them to coordinate resources and capabilities efficiently and thereby increase competitiveness (Borda et al., 2017). In addition, they function as platforms for internationalisation, supported by good corporate governance based on continuous learning, which facilitates their expansion (Aguilera et al., 2017).

2.2 AI Adoption

The adoption of AI is understood as the process by which intelligent systems are integrated in a detailed and sustained manner into organisations. Likewise, the assimilation of AI refers to the use and regularisation of technologies to improve processes and drive innovation in companies (Abdul Wahab & Radmehr, 2024).

2.3 Organizational Preparedness

When AI is integrated into an organization, advanced technologies are needed to support it (Haq & Suki, 2025). Organizational preparedness demonstrates how leadership and dynamic capabilities manage to adapt to changes and innovative technologies (Arroyabe et al., 2024). Before implementation, both technical and fundamental aspects must be reviewed (Hradecky et al., 2022).

2.4 AI Security

A particularly important feature of AI is confidentiality, which is supported by security, since when technologies prove their reliability, this promotes their use in the workplace (Valtonen et al., 2025). In addition, compatibility between systems and platforms is key to smooth adoption (Urbani et al., 2024). As is the perception of protection and competence that makes up what is known as cognitive trust (Shamim et al., 2023).

2.5 Availability of financial support

Having adequate financial support allows an organisation to access the resources necessary to cover the costs of technological implementation (Haq & Suki, 2025). This also means having sufficient funds to invest in infrastructure that facilitates the integration of innovative solutions (Abdul Wahab & Radmehr, 2024). In turn, it means having the financial resources required to meet the excessive costs associated with AI adoption (Cooper, 2025).

2.6 Perceived employee capability

Employees' perception of their own digital competence directly affects their willingness to adopt AI. This is reinforced by their confidence in the reliability of the systems, which influences their willingness to use

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them and generate value (Shamim et al., 2023). Likewise, continuous education and training programmes are essential for employees to adapt to technological changes (Muehlemann, 2025).

2.7 AI-driven marketing

As a strategic differentiator, AI-driven marketing is associated with competitive advantages in dynamic markets (Haq & Suki, 2025). This positioning is supported by clear operational mechanisms such as segmentation, personalisation and real-time decisions enabled by algorithms and predictive analytics (Holmström & Carroll, 2025). In terms of innovation, AI accelerates content generation, prototyping, and the development of competitive solutions, which can shorten cycles and increase responsiveness (Cooper, 2025).

2.8 Perceived usefulness and perceived ease of use

Technological readiness paves the way by highlighting practical benefits and strengthening confidence in the application of AI among employees, as it reinforces staff perceptions (Hradecky et al., 2022). On that basis, perceived usefulness and perceived ease of use express the assessment of the benefits and simplicity of digital tools, directly influencing their acceptance (Haq & Suki, 2025). When these tools show clear improvements in performance and operational results, perceived usefulness is consolidated, which significantly favours adoption and sustained use (Mikalef et al., 2023).

2.9 Process innovation and product innovation

An organisation's effectiveness and its ability to provide more competitive products and services depend on its degree of innovation (Haq & Suki, 2025). In this process, the adoption of AI plays a fundamental role in improving operational management, changing business models, and creating new opportunities (Peretz-Andersson et al., 2024). Thus, AI fosters innovation by promoting the development of new products and the continuous optimisation of existing processes (Roberts & Candi, 2024).

2.10 Perceived customer pressure and perceived competitive pressure

In highly competitive markets, organisations are forced to innovate every year to keep up, making AI a key strategy in the competitive environment (Arroyabe et al., 2024). At the same time, customer expectations for fast, personalised, and efficient responses intensify the adoption of technologies (Haq & Suki, 2025). Recent evidence shows that this dual pressure from the market and customers accelerates the incorporation of agile and adaptive solutions for organisations (Jorzik et al., 2024).

2.11 Hypothesis development

Hypothesis creation is based on theories that explain how people adopt technology, considering the interaction between technological, organisational, and human factors, as well as recent research on AI. Other studies suggest that both technological and organisational readiness play a fundamental role in the acceptance and effective use of these tools (Jorzik et al., 2024). Based on the above, the following hypotheses are formulated:

H1: PEOU positively influences AIA.
H2: PU positively influences AIA.

Evidence shows that when workers consider technology to be easy to use, their intention to adopt it increases (Hendricks et al., 2023). In emerging markets, ease of use combined with organisational benefits reinforces the intention to implement AI. Furthermore, other research highlights that perceived ease and usefulness are key factors in the acceptance of AI in work environments (Kelly et al., 2023). Likewise, when the qualities of AI generate value in the organisation, commitment to sustained use over time is reinforced (Mikalef et al., 2023).

H3: OPR positively influences AI PU.

Organisational perception makes the usefulness of AI dependent on internal preparedness, such as resources and processes that facilitate the appreciation of the benefits of AI adoption (Haq & Suki, 2025). Additionally, internal conditions act as a frame of reference that shapes how emerging technologies are evaluated in different sectors, enhancing perceived usefulness (Rodríguez-Espíndola et al., 2022).

H4a: AFPS favours the PU of AI
H4b: AFPS favours the PEOU of AI.

In business contexts, the availability of financial support is associated with greater adoption of digital innovation, suggesting that it facilitates favourable perceptions of its value and use (Purnamasari et al., 2025). In turn, AI adoption is promoted through strategic management backed by financial flexibility, which strengthens the positive assessment of these technologies (Peretz-Andersson et al., 2024) (Hao et al., 2022).

Likewise, when training and development receive funding, confidence in adopting these technologies increases. Studies indicate that ongoing support, an adequate structure, and a well-prepared team directly contribute to AI being perceived as easier to use (Muehlemann, 2025).

H5a: PEC positively influences PU.
H5b: PEC positively influences PEOU.

Staff self-efficacy increases when AI is understood as a support that improves efficiency, raising its perceived usefulness (Hradecky et al., 2022). Ease of use is strengthened when processes are well structured and reliable data is available, facilitating implementation (Haq & Suki, 2025). In interactive environments, this perception acts as a bridge that makes AI valued as accessible and useful, especially when processes are properly aligned (Uren & Edwards, 2023).

H6a: PCP positively influences AI PU
H6b: PCP positively influences PEOU.

Organisations must respond quickly to improve and innovate their processes, as AI has become a key resource for increasing perceived utility (Cooper, 2025). Furthermore, its incorporation drives more adaptable business models, thereby strengthening competitive advantage (Jorzik et al., 2024).

At the same time, the pressure to remain competitive encourages investment in digitalisation, which reduces barriers to adoption and makes technology more accessible (Roberts & Candi, 2024).

H7a: PCPu increases the PU of AI.
H7b: PCPu increases the PEOU of AI.

PEOU is a key factor: when AI enhances the user experience by providing quick responses and continuous attention, the perception of value is strengthened (Urbani et al., 2024). In addition, teaching and providing a tailored service is associated with satisfactory performance and higher levels of satisfaction for employees (Olan et al., 2022). At the same time, this expectation for better experiences requires prioritising integrated and easy-to-manage solutions that must have clear interfaces, standardised processes, and operational support, which reduce technical complexity and increase the perception of usability. When design focuses on the user experience, interaction becomes accessible and predictable, reinforcing the idea of AI as a practical and easy-to-use technology (Roberts & Candi, 2024).

H8a: AIA drives PRI.
H8b: AIA drives PRI.

There is convincing evidence that AI tools shorten development times and speed up market adaptation, with visible effects on new product projects (Cooper, 2025). Their contribution is evident in three principal areas, starting with expanding idea generation, enabling design adjustments, and shortening testing and validation cycles; together, this increases the efficiency and competitiveness of the creative process (Haq & Suki, 2025). Furthermore, its ability to process large volumes of data and simulate scenarios strengthens early decision-making and supports product innovation (Roberts & Candi, 2024).

AI enables more agile processes through automation, advanced analytics, and cross-functional integration, which supports continuous improvement dynamics. In supply chains, AI-driven digitisation has strengthened logistics coordination and incorporated innovations that improve operational performance (Wei et al., 2024).

H9: AIA positively influences AIM in companies.

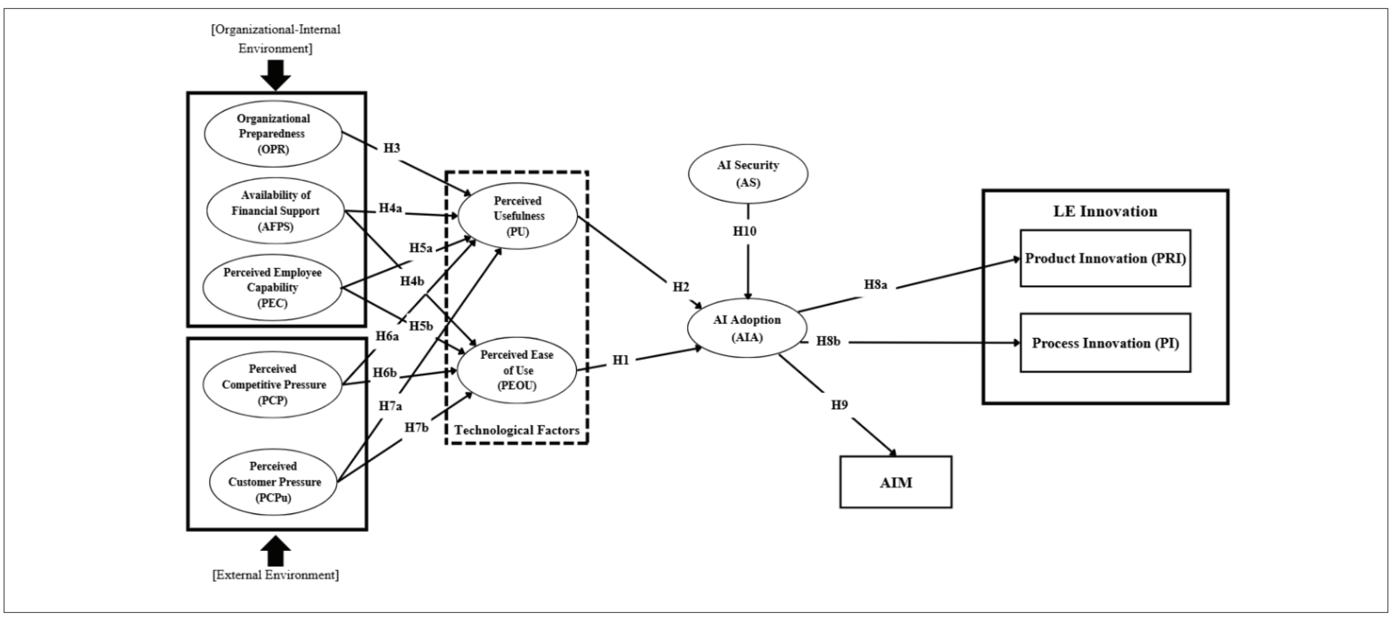
AIA improves the effectiveness of AIM, allowing organisations to manage and transform data into more accurate and automated action plans. Studies indicate that AIA improves organisational learning (Mohd Amin et al., 2025). Furthermore, it enables the development of new models that predict and reduce uncertainty in decision-making. This increases the maturity of the offering and marketing (Babina et al., 2024). AIA has been shown to improve the personalisation and automated approach of campaigns, as well as the prediction of consumer behaviour, elevating the role of marketing (Kumar et al., 2024).

H10: Greater AS increases AIA by strengthening user confidence.

The trust that employees have in AI is related to the levels of security that these technologies offer, which influences their willingness to use them in their daily work (Valtonen et al., 2025). Research shows that perceived security and clarity in how systems work reduce uncertainty and facilitate adoption, especially in high-pressure environments (Urbani et al., 2024). As frontline staff understand and trust the capabilities of AI, the conditions are created for greater and more sustained adoption of these tools (Shamim et al., 2023).

The conceptual model in Figure 1 shows the relationship between AI adoption and the variables that influence its implementation, as well as its effect on process optimisation. Each construct is articulated through hypotheses supported by literature, providing the theoretical basis that guides the study's analysis.

Figure 1. The theoretical model proposed and hypotheses



Source: Authors' own elaboration.

3. Materials and Method

3.1. Research design

This study was developed using a quantitative methodology with an inferential scope, proposing the Partial Least Squares Structural Equation Modelling (PLS-SEM), which was empirically validated through the application of a questionnaire focused on identifying the factors that influence the large telecommunications sector in the Peruvian context, characterized by promoting sustainable innovation and increasing competitiveness through strategic and efficient resource management.

Similarly, PLS-SEM is a technique geared towards the development of predictive models and the analysis of causal relationships between latent variables, based on covariance in more complex contexts or between moderate-sized samples (Huang, 2021). Thus, this technique is used as a method for exploring the variables of organisational readiness, availability of financial support, perceived employee capability, perceived competitive pressure, perceived customer pressure, perceived usefulness, perceived ease of use, AI-driven marketing, product innovation, process innovation, AI security, and AI adoption.

3.2. Instrument

The questionnaire was designed in two specific sections: the first section corresponds to the sociodemographic information of the surveyed sample; the second section describes the instrument that facilitates the analysis of the proposed connections between the constructs to be evaluated on a five-point Likert scale using statements that range from strongly disagree to strongly agree. The questionnaire was adapted from (Haq & Suki, 2025; Valtonen et al., 2025). *The questionnaire was conducted by an official translator who ensured that the items were understood in the context under investigation. A pilot test was then conducted with 25 people who met the sample inclusion criteria. To calculate the reliability of the instrument, Cronbach's alpha reliability coefficient was used, yielding a result of 0.727, indicating high internal consistency. The questionnaire design is published at the following link: https://doi.org/10.5281/zenodo.17595594*

3.3 Sample

The information used in this study was collected through a questionnaire distributed during the second half of 2025 to employees of five large telecommunications companies in Peru during that period. To ensure a sample size commensurate with the target population, the questionnaire was distributed to 371 potential participants, of whom 300 usable responses were received for analysis, indicating a response rate of 80.86%, which according to research is valid and statistically acceptable. Participants gave their informed consent online after learning about the objectives and procedures of the study. The data were analysed anonymously and confidentially. The participants were individuals who support the use of AI to optimise processes, selected through non-probabilistic convenience sampling, a method commonly used in design studies and applied for its practicality and accessibility in real contexts (Cash et al., 2022). Furthermore, this type of sampling is useful in applied research stages, especially in contexts that are difficult to access (Ahmed, 2024). The survey was administered using Google forms.

The population N was estimated based on the total number of employees of five large telecommunications companies in Peru for the period 2025-10 registered with SUNAT (National Superintendency of Customs and Tax Administration), CLARO (N=3,396), MOVISTAR (N=3,226), ENTEL (N=1,873), BITEL (N=1,220) and WIN (N=1,174), obtaining a total of N=10,889 workers.

The minimum sample size for a finite population was calculated assuming a confidence level of 95% ($Z = 1.96$), a margin of error of 5% ($e = 0.05$) and maximum variability ($p = 0.5$; $q = 0.5$). First, the sample size for a large population was estimated: $n_0 = (Z^2 \cdot p \cdot q) / e^2 = (1.96^2 \cdot .5 \cdot 0.5) / 0.05^2 = 384.16$. Then the finite population correction was applied: $n = n_0 / [1 + (n_0 - 1) / N] = 384.16 / [1 + (384.16 - 1) / 10{,}889] = 371.10$, rounded to $n = 371$.

The study was conducted in the city of Lima, which was chosen for its suitability to represent a diverse population of telecommunications sector employees involved in the adoption of innovative technologies. Table 1 presents the sociodemographic information of the sample and additional details about the study.

Table 1. Sociodemographic questions

Indicator	Quanty	Percentage (%)
Total Participants	300	100%
Gender		**100.00%**
Male	172	57.33%
Female	128	42.67%
Prefer not to say	0	0.00%
Age Group		**100.00%**
18 - 24 years	42	14.00%
25 - 34 years	173	57.67%
35 - 44 years	76	25.33%
45 - 54 years	9	3.00%
55 years or older	0	0.00%
Academic Degree		0.00%
Complete secondary education	4	2.53%
Technical or institute degree	5	3.16%
Bachelor's degree	31	19.62%
University professional title	80	50.63%
Postgraduate – Master's	32	20.25%
Postgraduate – Doctorate	6	3.80%
Company Size		100.00%
Microenterprise (up to 10 employees)	0	0.00%
Small company (11 to 100 employees)	0	0.00%
Medium company (101 to 200 employees)	0	0.00%
Large company (more than 200 employees)	300	100.00%
Work Area		100.00%
General administration / Secretariat / Administrative assistance	19	6.33%
Accounting	9	3.00%
Finance / Treasury	20	6.67%
Human Resources	40	13.33%
Purchasing / Procurement	24	8.00%
Logistics / Warehouse / Distribution	17	5.67%
Customer service / Front desk / Call center	36	12.00%
Sales administrative support / Commercial	42	14.00%
Marketing	35	11.67%
IT / Systems / Support (administrative function)	16	5.33%
Legal / Compliance	11	3.67%
Planning / Projects / PMO	28	9.33%
Management / Executive (administrative role)	3	1.00%
Other	0	1.90%
AI Usage Frequency		100.00%
Never	2	0.67%
Almost never	7	2.33%
Sometimes	20	6.67%
Almost always	106	35.33%
Always	23	7.67%
		100.00%

3.4. Data processing and instrument

To analyse the data obtained, the PLS-SEM method was used with SmartPLS 4 software, which allowed the relationships proposed in the model to be evaluated (Ringle et al., 2023). In this way, the convergent validity, discriminant validity, and reliability of the constructs were verified (Hauff et al., 2024).

Convergent validity was also examined using external loadings, as well as internal and composite reliability. These criteria were evaluated following recent guidelines that propose good practices and a clear explanation of the method.

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4. Analysis of results

4.1. Measurement model

Convergent validity shows how well the indicators represent the same construct and helps to confirm that the model measures what it should measure.

Table 2 presents the convergent validity statistics for the measurement model. It includes the factor loadings that meet the established criteria and the VIF values, which confirm that there is no multicollinearity affecting the internal validity of the model.

The literature indicates that VIF values should not exceed 5. Another criterion considered is the average extracted variance (AVE), which indicates whether the construct explains more than half of the variance of its indicators. In addition, the construct is expected to share greater variance with its own indicators than with those of other constructs, so values greater than 0.5 are recommended (Alamer, 2022).

Table 2. Convergent validity of the model

Indicator	Outer Loadings	VIF	AVE	CA	CR
AFPS 1	0.936	2.027	0.855	0.832	0.922
AFPS 2	0.913	2.027			
AIA 1	0.880	1.906	0.720	0.806	0.885
AIA 2	0.820	1.698			
AIA 3	0.845	1.691			
AIM 1	0.787	1.629	0.590	0.767	0.851
AIM 2	0.684	1.334			
AIM 3	0.756	1.438			
AIM 4	0.837	1.702			
AS 1	0.769	1.383	0.571	0.752	0.842
AS 2	0.720	1.443			
AS 3	0.750	1.368			
AS 4	0.783	1.594			
OPR 1	0.898	1.530	0.794	0.741	0.885
OPR 3	0.885	1.530			
PCP 1	0.826	1.499	0.659	0.741	0.853
PCP 2	0.811	1.460			
PCP 3	0.798	1.460			
PCPu 1	0.862	1.851	0.700	0.789	0.874
PCPu 2	0.761	1.519			
PCPu 3	0.882	1.717			
PEC 1	0.826	1.605	0.677	0.761	0.863
PEC 2	0.826	1.564			
PEC 3	0.816	1.473			
PEOU 1	0.856	1.256	0.726	0.622	0.841
PEOU 3	0.848	1.256			
PI 1	0.822	1.558	0.632	0.709	0.837
PI 2	0.735	1.293			
PI 3	0.824	1.425			
PRI 1	0.831	1.257	0.725	0.622	0.841
PRI 3	0.872	1.257			
PU 1	0.812	1.205	0.705	0.584	0.827
PU 2	0.867	1.205			

Source: Prepared by the authors using SMART-PLS.

Internal consistency was assessed using Cronbach's alpha (CA) and composite reliability (RC), which allows the reliability of an instrument whose items seek to measure the same construct or latent dimension to be estimated.

CA and CR values range from 0 to 1; the closer to 1, the greater the internal consistency between items. When items are positively correlated, the variance of the sum increases, reaching a value of 1 if all items were perfectly correlated. Conversely, if they were completely independent, there would be no relationship between them (Frías-Navarro & Pascual Soler, 2012). The interpretation of these values follows different guidelines, although the most used are: <0.50, unacceptable; 0.50–0.59, poor; 0.60–0.69, questionable; 0.70–0.79, acceptable; 0.80–0.89, good; and 0.90–1.00, excellent (Gliem & Gliem, 2003).

As a general criterion, measurements of the same construct must show high correlations to ensure convergent validity, while correlations between different constructs must be lower to ensure discriminant validity (Cheung et al., 2023). In this study, discriminant validity is assessed using the Heterotrait-Monotrait (HTMT) ratio matrix, which shows that this criterion is met for the measurement model, thus maintaining that the model is dependable and valid in convergent and discriminant terms.

Table 3. Heterotrait-Monotrait (HTMT) ratio matrix

	AFPS	AIA	AIM	AS	OPR	PCP	PCPu	PEC	PEOU	PI	PRI	PU
AFPS												
AIA	0.832											
AIM	0.627	0.607										
AS	0.479	0.638	0.603									
OPR	0.880	0.870	0.616	0.595								
PCP	0.721	0.643	0.664	0.529	0.769							
PCPu	0.668	0.669	0.731	0.625	0.819	0.854						
PEC	0.756	0.782	0.608	0.550	0.844	0.795	0.731					
PEOU	0.721	0.773	0.815	0.714	0.806	0.691	0.734	0.852				
PI	0.685	0.595	0.750	0.653	0.611	0.710	0.625	0.625	0.822			
PRI	0.721	0.657	0.828	0.706	0.720	0.715	0.683	0.703	0.790	0.796		
PU	0.695	0.627	0.695	0.705	0.821	0.871	0.742	0.838	0.758	0.757	0.862	

Source: Prepared by the authors using SMART-PLS.

4.2. Structural model

The evaluation of relationships in the structural model is performed using path coefficients. To do this, path values, T-values, and p-values are used, calculated using the bootstrap method in SmartPLS 4, considered the most widely used procedure for estimating standard error. According to the literature, a p-value ≤ 0.05 indicates statistical significance at 95%, so the hypothesis is accepted when it meets this criterion. Likewise, the T-value functions as a p-test, whose threshold is set at 1.96 (Kock, 2016). The results are shown in Table 4 and show that 10 of the 15 hypotheses proposed for the model are met.

Table 4. Hypothesis testing

Hypothesis		Path Value	STDEV	T Value	P value	Acceptance
AFPS -> PEOU	H4b	0.1882	0.0800	2.3520	0.0187	Accepted
AFPS -> PU	H4a	0.0460	0.0737	0.6238	0.5328	Rejected
AIA -> AIM	H9	0.4814	0.0661	7.2851	0.0000	Accepted
AIA -> PI	H8b	0.4569	0.0786	5.8125	0.0000	Accepted
AIA -> PRI	H8a	0.4697	0.0596	7.8797	0.0000	Accepted
AS -> AIA	H10	0.2643	0.0712	3.7127	0.0002	Accepted
OPR -> PU	H3	0.1595	0.0880	1.8134	0.0698	Rejected
PCP -> PEOU	H6b	0.0191	0.1043	0.1836	0.8544	Rejected
PCP -> PU	H6a	0.2620	0.0781	3.3553	0.0008	Accepted
PCPu -> PEOU	H7b	0.2216	0.0915	2.4228	0.0154	Accepted
PCPu -> PU	H7a	0.0920	0.0820	1.1219	0.2619	Rejected
PEC -> PEOU	H5b	0.3336	0.1135	2.9400	0.0033	Accepted
PEC -> PU	H5a	0.2230	0.1150	1.9394	0.0525	Rejected
PEOU -> AIA	H1	0.3533	0.0819	4.3153	0.0000	Accepted
PU -> AIA	H2	0.1501	0.0714	2.1023	0.0356	Accepted

Source: Prepared by the authors using SMART-PLS.

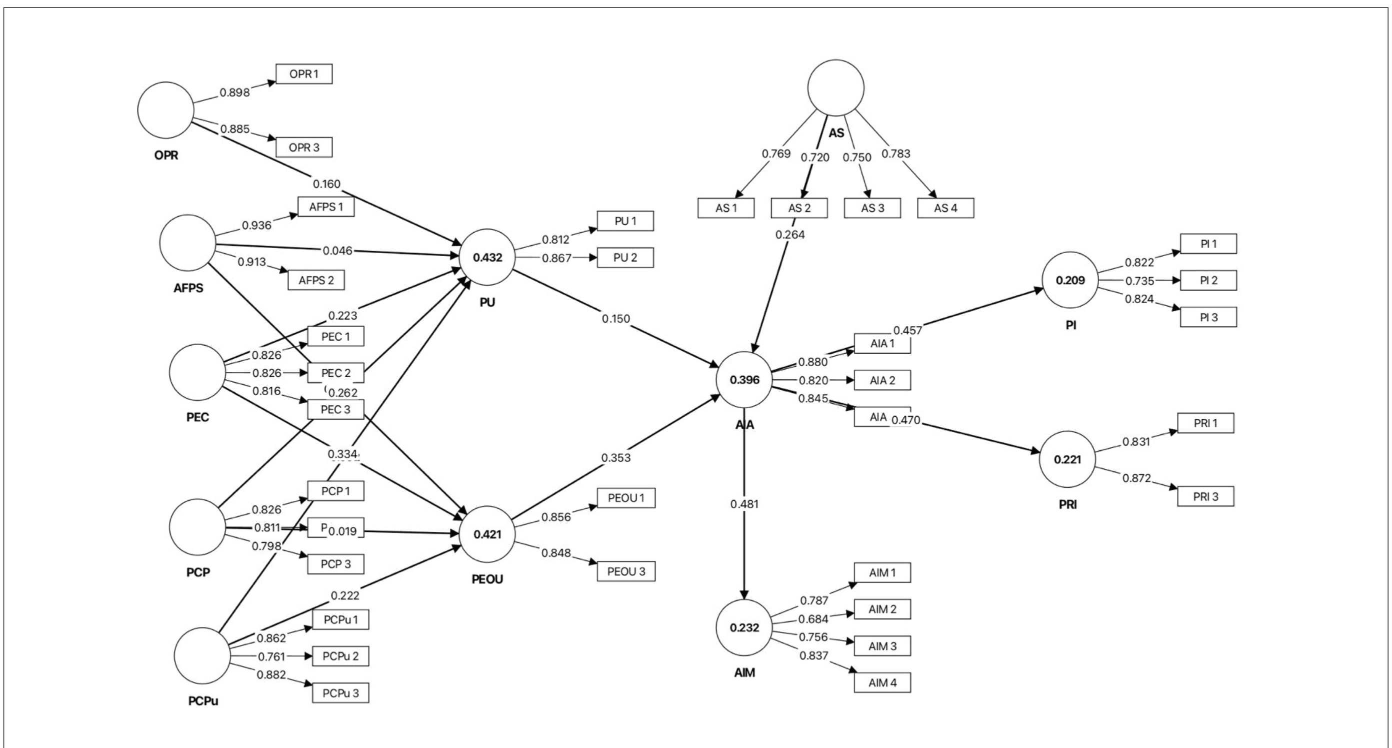
The results show that perceived usefulness, perceived ease of use, and AI security have a positive impact on AI adoption in the telecommunications sector in Peru. Based on this, AI adoption has a significant impact on product innovation, process innovation, and AI-driven marketing. To support the results from a predictive approach, R^2 is evaluated, which represents the proportion of total variance explained, as shown in Figure 3. The literature indicates that values of 0.25 are considered weak, 0.50 moderate, and 0.75 substantial to support the predictive capacity of endogenous variables (Astrachan et al., 2014). The moderate variables are AI adoption with a value of 0.546, perceived ease of use with a value of 0.571, and perceived usefulness with a value of 0.582.

The results relate to technological acceptance in information-intensive organisations, such as telecommunications, where, as an employee, the benefits are clear in terms of utility, low operational friction, ease of use and trust and control of the associated risk. It is therefore understandable that AI-related security is an important precursor to its adoption in this field, as exposure to sensitive data and decision automation increases the level of trust required for the use of AI technologies. Findings indicate that usefulness and ease of use are direct determinants of intention to use digital services (Verástegui et al., 2025). Acceptance is affected by risk-related perceptions, reinforcing the idea that security and data governance are crucial for the actual use of technology in the workplace (Baviera & Marín-Pérez, 2025). Long the same lines, the digitisation of emerging economies highlights that digital maturity often requires a higher level of cybersecurity and coordinated technology adoption, supporting the idea that security acts as a driver of adoption when organisations seek to scale AI without damaging their reputation (Manzo-Martínez et al., 2025).

The size of the f^2 effects for each relationship was also evaluated for predictive purposes. The literature indicates that values between 0.02 and 0.15 represent small effects, between 0.15 and 0.35 medium effects, and values above 0.35 large effects (Legate et al., 2023). The relationships: AI adoption → AI-driven marketing (0.302) obtained medium effects; AI adoption → Process innovation (0.264) obtained medium effects; AI adoption → Product innovation (0.283) obtained medium effects; AI security → AI adoption (0.228) obtained medium effects; and Perceived competitive pressure → Perceived usefulness (0.057) had a small effect; and Perceived customer pressure → Perceived ease of use (0.042) had a small effect; and Perceived employee capability → Perceived ease of use (0.099) had a small effect; and Perceived collaborator capability → Perceived usefulness (0.042) had a small effect; and Perceived ease of use → AI adoption (0.143) had a small effect; and Perceived usefulness → AI adoption (0.026) had a small effect.

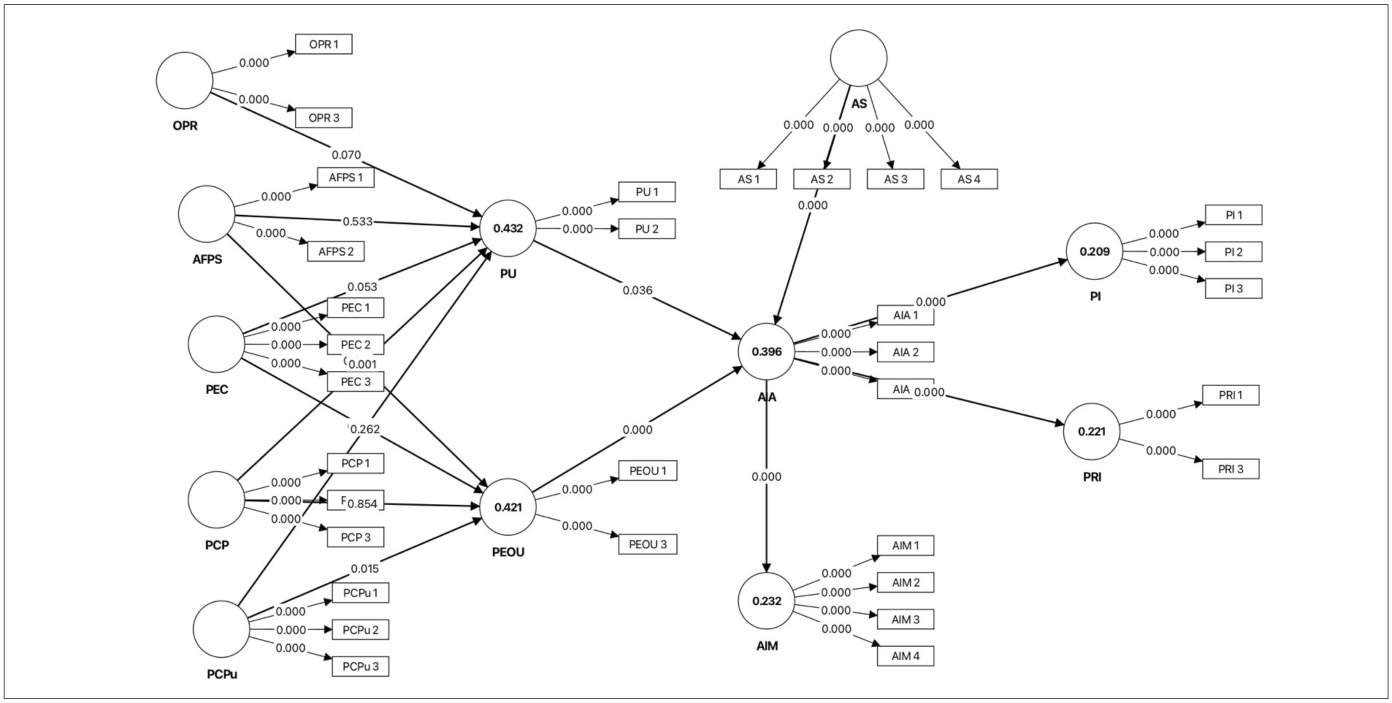
On the other hand, the results are also presented in the SmartPLS graph, as shown in Figure 2.

Figure 2. Results of the model produced by the SmartPLS programme.



Source: Output generated using SmartPLS software.

Figure 3. Bootstrapping



Source: Output generated using SmartPLS software.

Also, as a last predictive indicator, the Q^2 value was examined. This is considered relevant when it is greater than 0 in the cross-validation redundancy report, indicating that the model has predictive power. In addition, values of 0.02, 0.15, and 0.35 reflect small, medium, and large predictive relevance, respectively (Kock, 2016). Thus, endogenous variables such as AI adoption (0.457), perceived usefulness (0.391) and perceived ease of use (0.372) have high predictive relevance. while the variables AI-driven marketing (0.239), process innovation (0.223) and product innovation (0.239) have a medium predictive impact. This demonstrates that the model proposed in this study meets the criteria of validity and construction and demonstrates predictive relevance.

The moderate R^2 values obtained for adoption and its associated constructs are also consistent with previous studies analysing organisational outcomes derived from digital capabilities and transformation processes. The literature shows that digital transformation, in its multiple dimensions, at least in terms of effective technology adoption, has positive and significant outcomes (Niyawanont et al., 2022). Thus, in this research, AI adoption can explain and predict results in process innovation, product innovation, and AI marketing, which is reasonable given that these technologies are new. Previous research has analysed decision-making approaches and predictive modelling, reinforcing the idea that adoption is a multi-causal phenomenon with a subsequent impact on results (Portocarrero-Sierra et al., 2025).

Finally, from an innovation management perspective, qualitative results indicate that there is an assembly of capabilities, team skills, and technological infrastructure that support innovation and results (Ibujés-Villacís & Franco-Crespo, 2022).

5. Discussions

This study thus supported the first hypothesis that perceived ease of use positively influences AI adoption ($\beta=0.353$; $p=0.000$). The results showed that the clearer and simpler the tool, the greater the willingness of users to adopt it. These findings are consistent with previous evidence, which indicates that ease of use is a key factor in the intention to adopt AI-based technologies (Kelly et al., 2023).

The second hypothesis that perceived usefulness positively influences AI adoption ($\beta=0.150$; $p=0.036$) was supported. The results suggest that when employees perceive clear benefits and improvements in their performance, their willingness to use AI-based tools increases. This relationship is consistent with recent evidence highlighting perceived usefulness as a key factor in the continuity and adoption of AI technologies (Ismail & Joshy, 2025; Jeong et al., 2025).

The third hypothesis, that organisational readiness positively influences the perceived usefulness of AI ($\beta=0.160$; $p=0.070$), was not supported. Therefore, the internal capabilities of the organisation do not necessarily determine the perceived usefulness of these tools. This result differs from the findings of previous studies, which have found that organisations with higher levels of readiness tend to perceive greater utility in the adoption of AI (Arroyabe et al., 2024; Hradecky et al., 2022).

H4a, which states that the availability of financial support favours the perceived usefulness of AI ($\beta=0.046$; $p=0.533$), was rejected. However, H4b, which states that the availability of financial support favours the perceived ease of use of AI, is supported. These results suggest that financial support does not necessarily increase the perception of usefulness, but it does make it easier for users to interact with the technology because it allows them to access infrastructure and tools that reduce barriers to use. This interpretation is consistent with studies that highlight that greater financial resources favour the effective implementation of AI and simplify its operational adoption (Hao et al., 2022; Peretz-Andersson et al., 2024).

H5a, which states that the perceived ability of the collaborator positively influences the perceived usefulness of AI (β=0.223; p=0.053), was rejected. However, H5b, which states that the perceived ability of the collaborator positively influences the perceived ease of use (β=0.334; p=0.003), is supported. These results suggest that, although collaborator skills do not directly increase perceived usefulness, they do reduce perceived complexity and facilitate interaction with technology. This would indicate that ease of use depends more on individual competencies, while perceived usefulness is linked to the benefits obtained (Mikalef et al., 2023; Uren & Edwards, 2023).

H6a, that perceived competitive pressure positively influences the perceived usefulness of AI (β=0.262; p=0.001), was supported. However, H6b, which states that perceived competitive pressure positively influences perceived ease of use (β=0.019; p=0.854), was rejected. This indicates that although competition drives organisations to recognise the strategic value of AI, it does not necessarily make it perceived as easier to use. The perception of ease of use seems to depend more on internal capabilities and prior experience than on external pressures. Studies agree that competition encourages the valuation of AI as a key resource but does not reduce its perceived complexity (Jorzik et al., 2024; Roberts & Candi, 2024).

H7a, that perceived customer pressure increases the perceived usefulness of AI (β=0.092; p=0.262), was rejected. However, H7b, that perceived customer pressure increases perceived ease of use (β=0.222; p=0.015), was supported. This suggests that while customer expectations do not raise perceived value, they do prompt organisations to adjust AI implementation to make it simpler and more accessible. Such an effect may be related to design improvements or increased user support. Different studies indicate that external demands can stimulate the adoption and simplification of technologies (Olan et al., 2022; Roberts & Candi, 2024).

H8a, which states that AI adoption drives product innovation (β=0.470; p=0.000), and H8b, which states that AI adoption drives process innovation (β=0.457; p=0.000), were supported. This indicates that the incorporation of AI favours the generation of new products and the improvement of internal processes by enabling analytical and operational capabilities that improve the efficiency and innovative potential of organisations. Recent evidence recognises AI as a driver of innovation in multiple dimensions, reinforcing its strategic role in organisational development (Cooper, 2025).

The ninth hypothesis that AI adoption positively influences digital marketing development was supported (β=0.481; p=0.000). This indicates that AI integration improves processes, including the ability to segment audiences, personalise messages, and automate campaigns, which improves overall marketing performance. Research indicates that AI alters the management and execution of marketing activities and enables more efficient and focused practices (Haleem et al., 2022; Kumar et al., 2024).

The study supported the tenth hypothesis that greater AI security increases AI adoption by strengthening user confidence (β=0.264; p=0.000). This result is particularly relevant in the Peruvian context, where the adoption of AI-based technologies is taking place in environments characterised by higher levels of institutional uncertainty, regulatory frameworks still in consolidation, and a high perception of risk associated with the use of automated systems. Unlike developed economies, where trust in digital infrastructure and data governance mechanisms is more consolidated, in the Peruvian context, AI security becomes a crucial factor in legitimising its use in administrative processes, especially when these involve sensitive information and automated decisions. Previous studies argue that, in these contexts, transparency and understanding of how AI systems work are key elements in reducing the perception of risk and promoting organisational acceptance (Zerilli et al., 2022).

From a theoretical perspective, this finding reinforces the role of cognitive trust as a key mechanism in the adoption of AI. Employee trust is not built on emotional acceptance of technology, but rather through rational assessments of its reliability, transparency, data protection capabilities, and operational control (Shamim et al., 2023). In this sense, AI security acts as an enabler that reduces the perception of risk and promotes more sustained adoption of these tools. When AI systems are perceived as secure, employees are more willing to integrate them into their administrative routines, which facilitates their incorporation into workflows and contributes to the optimisation of administrative processes. Recent evidence indicates that the combination of security, transparency, and cognitive trust is crucial for consolidating the organisational adoption of AI and translating it into operational and innovative improvements, especially in complex business contexts (Glassberg et al., 2025; Valtonen et al., 2025).

The results show that the adoption of AI depends on perceptions such as ease of use, usefulness, employee capacity, and security, which strengthen trust and motivate its use. In addition, AI drives innovation and marketing, while external factors have more limited effects.

6. Limitations and future research

Although the research provides empirical evidence on AI and its influence on large corporations, it has limitations that need to be considered. The cross-sectional quantitative design only provides a view of the current state of artificial intelligence adoption and related perceptions, without facilitating analysis of how these relationships change over time. Similarly, the findings are based on perceptions rather than operational indicators, so it would be appropriate to enrich surveys with objective data from internal systems. With regard to future research, longitudinal designs could be used to follow employees and organisations through different stages of implementation, as well as

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incorporating variables such as previous experience with technology, digital maturity, resistance to change, or even ethical factors related to the use of AI, in order to enrich the model and delve deeper into the determinants that influence its adoption and the effects it generates within organisations.

7. Implications of the study

The results of the study offer important implications for the management of large telecommunications companies seeking to leverage AI to optimise processes and drive innovation. It confirms that perceived ease of use, perceived usefulness, and employee capabilities are essential factors for adoption, so organisations must prioritise the design of intuitive tools, accompany them with clear communication of their benefits, and strengthen digital skills through progressive training programmes. Likewise, it is evident that AIA drives product and process innovation and data-driven marketing, underscoring the need to integrate these technologies into portfolio management and strategic decision-making through multidisciplinary teams that bring together technology, data, and customer experience. Finally, AI security emerges as a key element in strengthening trust and encouraging adoption, which requires clear data protection policies, bias monitoring, and transparent communication that reduces the perception of risk.

8. Conclusions

The evidence obtained indicates that, in large telecommunications companies in Peru, the adoption of AI is a central axis between the technological preparedness of the organisation, employee perceptions and innovation outcomes. The PLS-SEM model confirms that perceived ease of use, perceived usefulness, and trust in AI are the key determinants of adoption: when solutions are intuitive, clearly beneficial to task performance, and dependable, employees are willing to incorporate them into their daily routines. Indirectly, the availability of financial resources, employees' perceived capabilities, and competitive and customer pressure contribute to adoption by reducing barriers to use and forcing organisations to optimise and calibrate their implementation.

Carefully and in detail, the results show that effective AI adoption impacts product innovation, process innovation, and AI-powered marketing. These three dimensions function as special mechanisms for administrative improvement, reducing cycles. Improved efficiency and responsiveness to a competitive market are achieved through improved internal coordination, personalised offerings, and the use of a data-driven decision-making system. Based on the information and data collected in the study, simply declaring that "organisational readiness" exists or having financial resources available is not enough; where a real impact on the perception of usefulness is needed, the framework of conditions must be expanded to include a system of simple tools, continuous training, and established security.

Overall, the article provides an integrated framework that connects the literature on technology acceptance, organisational readiness, trust in AI, and innovation outcomes in an unexplored Latin American context. For telecommunications companies, the findings suggest that the path to optimising administrative processes through AI involves three priorities: user-centred solution design, sustained investment in digital skills development, and a robust algorithmic security and governance policy. While the results are limited to a specific sector and period, they provide an empirical basis for other organisations in emerging economies to re-evaluate their AI adoption strategies and guide them towards a more efficient, innovative, and reliable administrative transformation.

Credit authorship contribution statement

Author 1: Writing original draft – review & editing, Conceptualisation, Data curation.

Author 2: Writing original draft – review & editing, Conceptualisation, Data curation.

Author 3: review & Methodology, Software validation. Funding

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Declaration of competing interest

There is no conflict of interest to declare.

Data availability -> ZENODO

The data supporting this research can be archived and made available on Zenodo under the following DOI: 10.5281/zenodo.17595594

Consent to participate

Informed consent was obtained from all participants.

Ethical statement

The study design was approved by the Ethics Committee of the Administration programme of the Faculty of Business Sciences of the Universidad San Ignacio de Loyola (USIL) prior to data collection (USIL-FCE-A-2025-49). All participants provided informed consent.

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