



STRATEGIC INTEGRATION OF ARTIFICIAL INTELLIGENCE IN EDUCATIONAL QUALITY: DIAGNOSIS AND PROPOSAL FOR UNIVERSITIES IN AMAZONAS, PERU

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ABSTRACT

Artificial intelligence (AI) in higher education faces the challenge of translating technological adoption into effective improvements in educational quality, especially in contexts with infrastructural limitations such as Amazonas region, Peru. This research aligned with SDG 4 (quality education) and aimed to propose a model for integrating artificial intelligence into public policies to increase educational quality in public universities of Amazonas region. A basic study was developed with a quantitative approach, non-experimental cross-sectional design, and propositional scope. The sample included 365 participants (students and faculty) from UNTRM and UNIFSLB, selected through simple random probability sampling. A validated Likert-type questionnaire processed with SPSS 27 was applied. Results revealed a paradox: 98.4% reported medium-high levels of AI integration, but only 29.9% perceived high educational quality. The most deficient dimensions were equity (24.1% low), relevance (20.3% low), and effectiveness (20.8% low). It was concluded that high spontaneous AI adoption does not generate proportional improvements without clear institutional policies, systematic training, and ethical governance frameworks, justifying the proposed model of strategic integration into educational public policies, which was validated by experts.



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I. INTRODUCTION

Artificial intelligence (AI) is increasingly integrated into global higher education and acts as a driver of change in academic management. Universities that incorporate AI achieve more efficient processes and personalized learning experiences, with direct impact on student performance and resource administration [1]. The analysis of educational big data enables anticipation of academic outcomes and content optimization, which strengthens pedagogical and administrative decision-making [2]. This advancement connects with Sustainable Development Goal (SDG) 4, oriented toward inclusive, equitable, and quality education. Target 4.3 prioritizes equal access to higher education by 2030. Within this framework, AI supports sustainable management models, especially in public universities with budgetary limitations, and strengthens knowledge retention among students [3], [4]. The global Artificial Intelligence market in education reached USD 5.88 billion in 2024 and projects annual growth of 31.2% until 2030 [5]. Nearly half of universities have incorporated AI tools, primarily through chatbots and predictive analytics systems [6]. In the United States, automated teaching assistants have modified classroom dynamics in university settings. According to [7] demonstrated that perception of the evaluation system and ease of interaction with these assistants influence their acceptance by students. In Latin America, experiences in Mexico confirmed improvements in academic satisfaction and complex thinking development through AI-based platforms [8]. Despite these advances, barriers persist related to financing, lack of structural support and limited willingness to share data, as well as privacy concerns, which increase gaps between institutions [9], [10]. In Peru, the education system faces considerable challenges in quality and infrastructure, especially in rural areas. 92% of Peruvian households had internet access in 2023, with increases in rural areas to more than 80% from 41.5% in 2019 [11]. Strengthening competencies in information and communication technologies (ICT) is fundamental to incorporating AI into educational policies [12]. In 2021, only 13% of young Peruvians and adults possessed general ICT skills.

This figure represents the foundation for building educational policies that incorporate AI to improve quality in public universities. In Amazonas region, access to technological resources essential for implementing AI is unequal. The proportion of households with internet access reached 40.8% in 2023, but remains below the national average. The contrast between rural and urban areas regarding infrastructure influences technology adoption in educational settings. In 2017, only 70.3% of rural households in the region had electricity through the public grid [13]. These conditions accentuate challenges for incorporating AI into regional educational strategies. The limitations, combined with scarce faculty training, hinder the implementation of technological innovations. However, it has been demonstrated that intelligent tutors based on AI improve educational effectiveness [14]. The limited involvement of the academic community in adopting innovative technologies threatens educational excellence and regional sustainable development. When authorities, faculty, and students remain distant from technology adoption processes, a void is created that fills with context-disconnected decisions, resulting in ineffectiveness and affecting the essence of inclusive education [15]. It is essential that educational entities foster a culture of training and societal involvement around technology implementation. The benefits of AI must be explained, favoring creation of consultation mechanisms with students and professors, promoting clarity in implementation procedures, and establishing effective feedback systems. Active participation is a practical necessity to guarantee quality in education, enabling the forging of a more inclusive, effective educational system aligned with social needs. Considering the previously described problems, this research aimed to answer the following question: in what way will a model for integrating artificial intelligence into public policies increase educational quality in public universities of Amazonas region? The general objective was to propose a model for integrating artificial intelligence into public policies to increase educational quality in public universities of Amazonas region.

The specific objectives were: to diagnose the level of educational quality in public universities of Amazonas region, to develop a model for integrating artificial intelligence into educational public policies to increase educational quality in public universities of Amazonas region, and to validate the model for integrating artificial intelligence into educational public policies through expert judgment. The justification for this research is based on the need to improve educational quality in disadvantaged territories such as Amazonas region, in order to reduce access and equity gaps. From a theoretical perspective, the study contributes knowledge about integrating artificial intelligence into educational public policies, a field still in development phase. From a practical perspective, the proposed model offers an applicable alternative to strengthen teaching in public universities of Amazonas region through technological tools oriented toward monitoring and improving learning. It should be noted that AI also contributes to increasing student retention, a critical aspect in contexts with high dropout rates, as indicated by [16]. Additionally, the research's impact is expressed in its contribution to designing more inclusive educational policies, based on evidence, with capacity to respond to the territory's real needs. Strategic adoption of AI modifies academic and administrative processes [17]. In this sense, epistemological evidence of these advances maintains the need for models that integrate these technologies within educational public policies. Nevertheless, it is essential to know the level of technological adoption to design effective interventions [18], given that educational quality must be evaluated considering access to resources, an aspect enhanced by AI [19], since its use serves to extend knowledge effectively [20].

II. THEORETICAL REFERENCE

The incorporation of artificial intelligence in higher education configures a global phenomenon that modifies academic practices and optimizes learning personalization and institutional management. According to [21] indicate that modernization through AI enables individualizing teaching and managing resources with greater precision through automated and predictive processes, while [22] highlight its impact on evaluation systems, curricular personalization, and administrative management, with direct effects on equity and sustainability of educational services. This integration is inserted into a technoscientific logic oriented toward process optimization through algorithms that adjust contents, timing, and formative pathways according to each student's academic behavior. The Technology-Organization-Environment (TOE) Framework constitutes a reference point for analyzing AI inclusion in universities. In [23] explain that this model enables examining the influence of technological characteristics, organizational capabilities, and socioeconomic and normative conditions on new technology adoption, which facilitates identifying barriers and opportunities within the institution. Complementarily, the Conceptual Paradigm triangle proposed by [24] integrates technical, social, and ethical dimensions to examine opportunities, risks, and principles in AI use in teaching, a relevant aspect in contexts marked by digital gaps and structural limitations such as those present in peripheral territories. The AI Literacy Conceptual Framework, developed by [25], maintains that AI implementation in university settings must be based on faculty and students having an adequate level of artificial intelligence literacy, that is, acquiring the necessary skills to use intelligent systems ethically, critically, and productively. Along the same lines, the Ethical Governance and Data Protection Framework formulated by [26] establishes guidelines to protect privacy, reinforce equity, and ensure transparency in educational use of AI, which guides the formulation of technological governance policies focused on reducing risks, organizing data management, and guaranteeing more equitable access to artificial intelligence benefits in contexts such as Amazonas region.

The Technology Acceptance Model proposed by [27] explains technological adoption based on perceived utility and ease of use, variables that affect educational actors' attitudes toward incorporating new tools. This approach articulates with UNESCO's [28] Educational Quality theory, which defines excellence from the dimensions of relevance, effectiveness, equity, efficiency, and sustainability. It is complemented by [29] Knowledge Management theory through the SECI model (Socialization–Externalization–Combination–Internalization) and with the Socio-Technical Systems theory (STS) formulated by [30], expanded by [31] and supported by [32], which emphasizes the need to integrate technology and social dynamics to strengthen educational environments coherent with institutional reality. Artificial intelligence is understood as systems that simulate human cognitive capabilities, based on skills such as learning, reasoning, and problem-solving, to optimize educational learning processes [33]. Its dimensions are: machine learning for predicting academic performance [34], natural language processing through educational chatbots, and data analytics for timely pedagogical feedback. Educational quality in higher education is the degree to which universities achieve relevant, equitable, effective, efficient, and sustainable results according to [28], convergent with [35], who indicate its relevance and institutional sustainability. In Amazonas region, this means closing access gaps, increasing digital competencies, and ensuring employability.

Its dimensions are relevance, effectiveness, equity, efficiency, and sustainability, which are expanded with Artificial Intelligence that responds to performance [36] and will help fulfill SDG 4, given the urgency of equity in rural scenarios warned by [37].

III. METHODOLOGY

This research was developed as a basic study, as it sought to generate theoretical-practical knowledge [38]. A non-experimental and cross-sectional design was assumed, since it was carried out in a single period and without manipulation of study variables [39]. This design enabled collecting information about the educational context of 2025, obtaining quantitative data that responded to the problem statement with scientific rigor. The scope of the study was propositional. The study variables were artificial intelligence, viewed from its integration into public policies, and educational quality. Artificial intelligence, defined by [40] as strategic incorporation of tools such as intelligent tutoring and predictive analysis, was structured into dimensions of planning, technological implementation, and ethical governance. Educational quality, according to [28], was understood as achieving relevant, equitable, and sustainable results in education. The unit of analysis consisted of students and faculty belonging to public universities of Amazonas region: the Universidad Nacional Toribio Rodríguez de Mendoza de Amazonas (UNTRM) and the Universidad Nacional Intercultural Fabiola Salazar Leguía de Bagua (UNIFSLB). The established inclusion criteria were: being institutionally active public universities in 2025, having undergraduate programs in effect between 2023 and 2025, having updated records of enrollment and teaching staff, willingness to participate voluntarily, and basic access to digital means to respond to the instrument. The total population was 6,964 individuals, comprising 537 faculty and 6,427 students, according to data reported by both institutions for the 2025-I academic semester. The sample was selected through simple random probability sampling, ensuring that each individual had the same probability of being chosen [41]. 365 individuals were included in the sample, prioritizing accessibility and willingness of participants to obtain relevant and reliable information [42].

For data collection, the survey method was used, considering a structured questionnaire as the instrument that measured perceptions about educational quality (relevance, effectiveness, equity, efficiency, and sustainability) and AI integration (Artificial Intelligence acceptance, intelligent tutoring, predictive analytics, ethical governance and transparency, and language processing), using a five-point Likert scale and verified through Cronbach's Alpha coefficient ($\alpha = 0.880$). It was developed based on the Technology Acceptance Model (TAM), the Technology-Organization-Environment (TOE) Framework, the Ethical Governance and Data Protection Framework, UNESCO's Educational Quality Theory, and Socio-Technical Systems (STS) Theory. Instrument verification was carried out through evaluation by specialists who analyzed coherence, clarity, relevance, and theoretical adequacy of the items. To evaluate reliability, a pilot test was applied to a representative sample, with the objective of analyzing data obtained through application of Cronbach's Alpha coefficient [43], [44]. The instrument results were processed using SPSS (Statistical Package for the Social Sciences) version 27 software, given that it is a program widely used in social science research due to its efficiency in performing basic data analysis [45]. This enabled analyzing opinions of students and professors about educational quality and artificial intelligence incorporation, identifying key trends in emerging technology use.

IV. RESULTS AND DISCUSSIONS

IV.1 RESULTS

Results obtained through application of the validated instrument to 365 participants from public universities of Amazonas region during the 2025-I semester, processed with SPSS 27, are presented organized according to the global diagnosis of educational quality and analysis of its five constitutive dimensions according to the UNESCO (2008) model. Additionally, findings about the current level of artificial intelligence integration in these institutions are included. Table 1 presents the distribution of perceived levels of educational quality in public universities of Amazonas region. These findings reveal a concerning situation where 70.2% of participants perceive significant deficiencies in university educational quality. The predominance of the medium level (62.5%) suggests that, while institutions meet basic standards, there are important shortcomings that limit educational excellence. The percentage at low level (7.7%) represents 28 participants who experience critical educational conditions requiring immediate attention. This distribution confirms the stated problem regarding structural limitations of public universities in emerging contexts such as Amazonas region.

Table 1: Levels of Educational Quality.

Levels	N	%
High level	109	29,9%
Medium level	228	62,5%
Low level	28	7,7%

Source: Author, (2026).

Table 2, corresponding to the relevance dimension, presents low level (20.3%), which constitutes an alarming finding. One in five participants considers that university education has low relevance regarding demands of the labor and social context. The medium level, grouping 45.8% of participants, suggests that there is perception of partial disconnection between curricular contents and competencies required in the regional and national labor market. The perceived low relevance relates to outdated curricula, limited linkage with the productive sector, and limited incorporation of emerging digital competencies.

Table 2: Levels of Relevance.

Levels	N	%
High level	124	34,0%
Medium level	167	45,8%
Low level	74	20,3%

Source: Author, (2026).

Table 3 presents results of the effectiveness dimension, understood as the degree to which universities enable students to achieve established learning objectives and successfully complete their academic programs. Effectiveness presents a high percentage at low level (20.8%), indicating that approximately one in five participants considers that universities are not effectively enabling students to achieve proposed learning objectives. The predominance of medium level (44.4%) suggests that there are partial achievements, but also systematic deficiencies in teaching-learning processes that prevent full accomplishment of educational goals.

Table 3: Levels of Effectiveness.

Levels	N	%
High level	127	34,8%
Medium level	162	44,4%
Low level	76	20,8%

Source: Author, (2026).

Table 4 regarding equity shows that this constitutes the most critical dimension of the diagnosis, presenting the highest percentage at low level (24.1%) among all dimensions analyzed. Nearly one in four participants perceives that there are significant barriers preventing equitable access to quality educational opportunities. Only 29.3% perceive a high level of equity, the lowest percentage among all dimensions at this level. This finding is relevant in the context of Amazonas region, characterized by marked inequalities between urban and rural areas.

Table 4: Levels of Equity.

Levels	N	%
High level	107	29,3%
Medium level	170	46,6%
Low level	88	24,1%

Source: Author, (2026).

Table 5 presents results of the efficiency dimension, defined as optimization in use of human, financial resources, and infrastructure to achieve educational objectives. Data show that efficiency presents relatively more favorable results than other dimensions, with the highest percentage at high level (36.4%) along with sustainability. However, 63.6% of participants still perceive that there are deficiencies in management and utilization of available resources. The low level (18.4%) represents a significant proportion evidencing critical inefficiencies in some contexts or institutional processes.

Table 5: Levels of Efficiency.

Levels	N	%
High level	133	36,4%
Medium level	165	45,2%
Low level	67	18,4%

Source: Author, (2026).

Table 6 shows that sustainability emerges as the dimension with the most favorable results in the diagnosis, registering the lowest percentage at low level (12.6%) and one of the highest at high level (36.7%), along with efficiency. Nevertheless, the predominance of medium level (50.7%) reveals that, while there are institutional foundations enabling continuity of educational processes, limitations persist in consolidating continuous and adaptive improvement. The low-level group raises concerns regarding viability of some programs or policies in the long term.

Table 6: Levels of Sustainability.

Levels	N	%
High level	134	36,7%
Medium level	185	50,7%
Low level	46	12,6%

Source: Author, (2026).

Table 7 presents current levels of artificial intelligence integration in public universities of Amazonas region. The low percentage at low level (1.6%) indicates practically universal receptivity toward AI and evidences that institutions have initiated technological adoption processes with broad acceptance from the university community. The predominance of medium level (61.1%) suggests that, while AI integration is still incipient or partial in scope, there is considerable critical mass of users who have already experimented with AI tools in educational contexts. The high level (37.3%) represents more than one-third of participants, indicating that there is a substantial group perceiving advanced integration.

Table 7: Levels of Artificial Intelligence Integration.

Levels	N	%
High level	136	37,3%
Medium level	223	61,1%
Low level	6	1,6%

Source: Author, (2026).

IV.2 DISCUSSION

The findings of this research offer empirical evidence about the current state of educational quality and artificial intelligence integration in public universities of Amazonas region. The diagnosis reveals a paradoxical situation: while 98.4% of participants report medium or high levels of Artificial Intelligence integration, only 29.9% perceive high educational quality. Deficiencies are concentrated mainly in equity (24.1% low level) and relevance (20.3% low level). This discrepancy between technological adoption and educational improvement constitutes the interpretive axis of the analysis. The study evidences a 7.4% gap between high AI integration (37.3%) and high educational quality (29.9%). This result differs from that reported by [36], who developed an intelligent tutoring model in Peruvian universities achieving a 15% increase in student performance and significant reduction in dropout. The divergence suggests that spontaneous AI adoption in Amazonas region, without institutional articulation or planned pedagogical design, does not generate proportional improvements in educational quality. It contrasts with, who demonstrated that generative AI increased personalized learning by 22%, emphasizing the importance of faculty training as a mediating variable. Results show partial agreement with, who analyzed student perceptions about AI in universities of Peru, Ecuador, and Mexico. 70% of students reported 18% improvements in teaching personalization. The high receptivity toward AI observed in Amazonas region (98.4% at medium and high levels) coincides with this positive perception. However, warned of the absence of ethical approaches and contextual adaptation, deficiencies also present in the Amazonian context. This partial convergence confirms the need for public policies that articulate AI with pedagogy and faculty development. The most significant difference is observed when contrasting results with, who conducted a qualitative study on ChatGPT use in Costa Rican higher education. They demonstrated that generative AI increases student participation but identified as the main obstacle the lack of articulation between government, universities, and civil society. In Amazonas region, that same structural barrier exists: high technological integration coexists with deficiencies in equity, relevance, and effectiveness.

Regarding equity, the results (24.1% low level and 46.6% medium) differ from findings by, who demonstrated that AI-based resources reduced mental effort by 30% and improved learning. Their study was developed in a context with advanced technological infrastructure and universal internet access. In contrast, in Amazonas region, only 40.8% of households have internet connection and 70.3% of rural dwellings have public electricity. This structural gap confirms that cognitive benefits depend on technological equity, a persistent deficiency in the study region. Curricular relevance (20.3% low level and 45.8% medium) partially coincides with, who examined excellence assurance mechanisms in 29 accredited universities in Chile, concluding that AI-based tools prioritize quantity over quality of publications. In Amazonas region, results corroborate that need: perception of disconnection between training and labor demands suggests that technological adoption without pedagogical criteria maintains low curricular relevance. High receptivity toward AI (only 1.6% rejection) agrees with findings by, who analyzed incorporation of generative AI in 63 Peruvian university professors. 66.7% reported high integration, achieving 20% improvement in didactic material development. In Amazonas region, 61.1% present medium integration, reflecting spontaneous use without structured training. This coincidence between Peruvian contexts demonstrates that familiarity with generative tools has promoted massive adoption, though it still requires critical digital literacy. Results about complexity in the context of Amazonas region (40.8% internet access, 70.3% rural electricity, but 98.4% medium-high AI integration) find repercussion with the framework proposed by, who established that management empowerment through knowledge, financing, and support structures is fundamental. Findings confirm those challenges in Amazonas region, where adoption exists without management empowerment, systematic knowledge, or governance structures. Among the main methodological limitations, several factors are identified that condition interpretation of findings and their extrapolation to other educational contexts.

The cross-sectional design prevents establishing clear causal relationships between AI integration and educational quality, since measurement was performed at a single moment without longitudinal follow-up enabling observation of changes over time. This is compounded by dependence on self-reported perceptions through Likert-type scales, a scenario in which participants tend to overestimate their level of AI use or educational service quality. Also noted is the lack of disaggregation by type of actor and by institution, which restricts analysis of differences between faculty and students, as well as between UNTRM and UNIFSLB, while evaluation of AI integration as a global construct, without specifying tools, frequency of use, or pedagogical purposes, generates ambiguity in interpretation of levels achieved. Future research lines demand a more profound methodological approach that incorporates longitudinal or quasi-experimental designs with control groups, in order to establish causal relationships between structured AI implementation and improvements in specific dimensions of educational quality, with measurements at 6, 12, and 24-month intervals. It is also required to disaggregate analyses according to rural or urban origin, socioeconomic level, gender, age, and academic area to identify differentiated impacts, while qualitative studies through interviews, focus groups, and observation will enable recognizing cultural, psychological, and organizational barriers in pedagogical AI integration. It also proposes to evaluate components such as smart tutoring, predictive analytics, and AI literacy programs in isolation, as well as to make comparisons between universities in Amazon region and urban cities in Peru, or with institutions in other Latin American countries with similar characteristics. The main contribution of this study is to provide contextualized empirical evidence on the paradox between the high adoption of AI and the limited improvement in educational quality at public universities in Amazonas region. Three critical dimensions are identified where institutional disarticulation prevents translating technological receptivity into measurable educational improvements. These finding challenges technological determinism and reaffirms the need for public policies that strategically integrate technological, pedagogical, organizational, and ethical components.

IV.3 PROPOSAL

The present model arises from the need to address deficiencies in educational quality identified in public universities of Amazonas region. Results evidence medium or low levels of educational quality and high receptivity toward artificial intelligence. This adoption does not translate into proportional improvements, since 98.4% of participants report medium or high levels of AI integration while only 29.9% perceive high educational quality, with critical dimensions such as equity at 24.1% at low level, relevance at 20.3%, and effectiveness at 20.8%. This paradox shows a gap between technological availability and institutional capacity to generate concrete improvements.

The proposed model guides spontaneous adoption toward a comprehensive strategy that addresses these dimensions through clear policies, systematic training, and ethical governance frameworks, in line with SDG 4 and the needs of Amazon region as an emerging context. The model integrates seven strategic components to close gaps between technological adoption and educational quality. First, the Intelligent Tutoring System with adaptive platforms based on machine learning and offline modules for areas with intermittent connectivity. Second, the Predictive Analytics System with data mining algorithms that identify risk of dropout or low performance, generating early alerts. Third, the AI Literacy Program that develops digital, pedagogical, and ethical competencies at three levels: basic, intermediate, and advanced. Fourth, the Ethical Governance Framework with institutional committees, data protection protocols, algorithmic audits, and guidelines on AI use. Fifth, Digital Equity Strategies with community centers, connectivity scholarships, mobile devices, and multilingual resources. Sixth, the AI-Based Curricular Update System with employability analysis and competency recommendations. Seventh, the Continuous Evaluation System with indicator dashboards linked to the five quality dimensions. Implementation contemplates seven phases during seventy-six months organized sequentially. The Detailed Institutional Diagnosis phase (3 months) evaluates technological capabilities, infrastructure, and digital competencies through audits and focus groups.

The Technological Architecture Design phase (9 months) develops a modular platform with offline components, mobile interfaces, security protocols, and pilot tests with 10% of students. The Progressive Implementation of AI Tools phase (12 months) deploys intelligent tutoring, predictive analytics, and recommendation systems in 50% of academic programs, with continuous technical support. The Intensive Faculty Training phase (6 months) covers 80% of personnel through workshops and certifications. The Establishment of Ethical Governance phase (4 months) forms committees and defines protocols according to Law No. 29733. The Systematic Monitoring and Evaluation phase (24 months) includes quarterly evaluations. The Scaling and Replication phase (18 months) documents results and transfers the model to other universities. The estimated budget amounts to S/ 2,700,000 and is distributed by components: the Technological Platform with S/ 650,000 for design, development, servers, and maintenance; Faculty Training with S/ 350,000 for training 537 faculty members, materials, and certifications; Digital Equity Infrastructure with S/ 480,000 for 15 community centers, 300 mobile devices, and subsidized connectivity; the Intelligent Tutoring System with S/ 420,000 for development and integration; Ethical Governance and Data Protection with S/ 280,000 for committees, training, and audits; Monitoring and Evaluation with S/ 200,000 for dashboards and quarterly reports; Management and Implementation with S/ 320,000 for coordination, supervision, and contingencies throughout the seventy-six-month period.

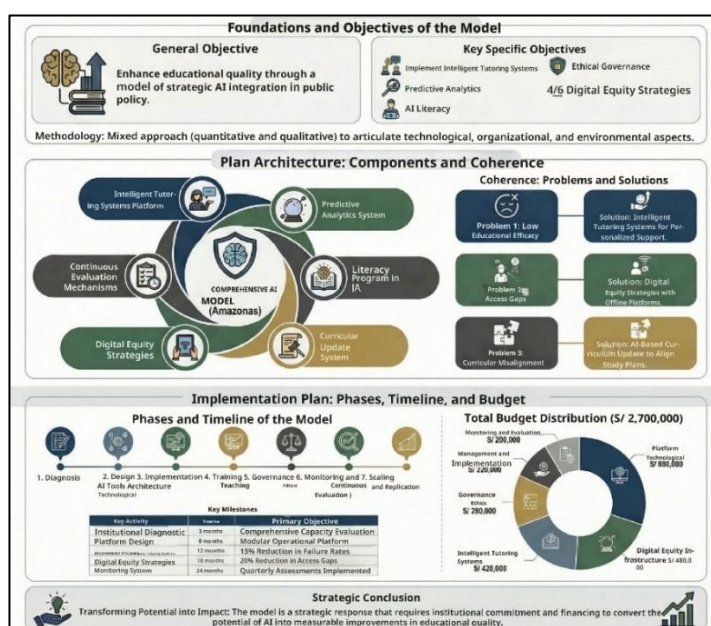


Figure 1: Model for integrating artificial intelligence into public policy to improve educational quality in public universities, Amazonas. Source: Author, (2026).

V. CONCLUSIONS

The diagnosis of educational quality in public universities of Amazonas region revealed significant structural deficiencies. Equity emerged as the most critical dimension, with barriers preventing equal access to quality educational opportunities, while curricular relevance presented alarming deficiencies, evidencing disconnection of university training from regional and national labor market demands, as did effectiveness. Additionally, the dimensions of efficiency and sustainability, although relatively more favorable, evidenced that the majority perceive deficiencies in resource management and institutional capacity to innovate. The model for integrating artificial intelligence into educational public policies responded strategically to identified deficiencies through systematic articulation of seven implementable phases, integrating technological, organizational, pedagogical, and ethical components. In turn, the proposal recognized particularities of the Amazonian context, incorporating solutions adapted to intermittent connectivity through platforms with offline components, interfaces optimized for mobile devices, and digital equity strategies. The strategic articulation between empirical diagnosis and intervention proposal enabled designing a contextualized model that transforms spontaneous AI adoption into strategic integration. Finally, findings evidenced a significant theoretical, methodological, and social contribution. Theoretically, the study challenged technological determinist assumptions by empirically demonstrating that high receptivity toward AI does not automatically generate proportional improvements in educational quality without mediation of contextualized public policies.

Methodologically, the research combined quantitative diagnosis with propositional design, generating a replicable model for Latin American public universities. Socially, the proposal aligned with SDG 4 by prioritizing equity as a critical dimension, developing personalization strategies through AI that compensate for structural disadvantages of rural students. This constitutes transferable knowledge to other Peruvian and Latin American public universities facing similar problems between expansion of access to emerging technologies and persistence of educational inequities.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Victor Manuel Valdiviezo Sir.

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Investigation: Victor Manuel Valdiviezo Sir.

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