Smart Pedagogical Strategies and Autonomous Learning in Higher Education in Peru

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***Abstract*—Autonomy and self-regulation among university students constitute key factors for the development of metacognitive skills and the strengthening of meaningful learning. In this context, the present study analyzes the relationship between Artificial Intelligence (AI)–based methodological strategies and the development of autonomous learning in higher education students. The objective was to predict and explain the variance of the constructs AI methodological strategies, autonomous learning, and academic development. A quantitative approach was adopted and implemented in two phases: an exhaustive theoretical review and the administration of an online survey to a sample of 383 university students from different academic disciplines. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS v4 software, yielding acceptable reliability levels ($\alpha \geq 0.70$). The results revealed significant and positive relationships between AI strategies, metacognitive processes, self-regulation, and affective motivation with academic development. Specifically, the use of virtual assistants was found to be strongly associated with AI methodological strategies ($\beta = 0.744$) and with academic development ($\beta = 0.212$), as virtual assistants enhance motivation by providing adaptive and personalized resources that stimulate autonomous learning. Furthermore, the mediating role of autonomous learning in the relationship between AI and academic performance was confirmed. These findings provide empirical evidence of the pedagogical use of AI as a facilitator of autonomous learning in university contexts. It is concluded that the integration of AI strengthens student autonomy, improves learning personalization, and optimizes academic performance; however, ethical and technological accessibility challenges persist and must be addressed to ensure equitable implementation in higher education.**

***Keywords*—education, artificial intelligence, chatbots, autonomous learning, students**

I. Introduction

Education is one of the fundamental pillars of human advancement and progress [1]. According to the United Nations Educational, Scientific and Cultural Organization (UNESCO), education contributes to a renewed vision of sustainable global development. In today's context of digital transformation, higher education faces the challenge of incorporating emerging technologies that strengthen instructional processes. Within this panorama, Artificial Intelligence (AI) has assumed a strategic role by becoming integrated into multiple phases of the teaching–learning process, with the aim of fostering student autonomy and promoting meaningful learning [2]. Despite the new opportunities offered by AI in education, its implementation remains challenging for most researchers and practitioners, particularly when developing relevant activities or systems within the sector [3], as it opens possibilities for redefining methodological teaching strategies [4]. AI is grounded in machine learning and uses algorithms to identify data patterns through three learning approaches—supervised, unsupervised, and reinforcement learning [5]. One of the central challenges lies in balancing automation with human intervention: although AI provides dynamic resources that reinforce conceptual understanding, its implementation must consider strategies that prevent teaching from being reduced to the mere reception of algorithm-generated responses [6].

Current university education often presents shortcomings, as institutions tend to implement fragmented systems, superficial content, and insufficient training, which hinder the genuine strengthening of students' cognitive competencies [7]. In this context, students experience a stage marked by constant technological progress and immediate access to information; therefore, they must be capable of critically understanding, analyzing, and applying such information, transforming it into meaningful learning that contributes to their personal development [8]. Consequently, educational institutions must adopt digital tools—such as adaptive platforms that are interactive and accessible—to meet the expectations of an active digital generation [9]. These platforms and automated evaluation systems personalize learning pathways according to individual needs and performance, promoting user engagement and supporting knowledge consolidation [10].

AI in education currently offers a wide range of possibilities for both instructors and learners within the teaching–learning process [11]. With the rapid advancement of AI, its use in education has increased significantly, providing adaptive learning, flexible assessment, and online learning experiences [12]. Personalized learning through AI enables approaches tailored to students' diverse and specific needs, thereby optimizing the teaching process more efficiently [13]. The adoption of AI not only enables universities to remain competitive at the global level but also enhances educational quality and innovation [14]. Several studies indicate that AI has experienced exponential growth in the global educational sector, offering algorithm-based solutions that optimize instruction and feedback and enabling more personalized and efficient learning experiences [15, 16]. This technological advancement has generated a substantial shift in traditional pedagogical dynamics by providing educators with new didactic tools and transforming how students access, process, and apply knowledge, with positive impacts on the improvement of existing educational models [17]. Effective integration of AI requires planned and continuous training processes that incorporate technical, pedagogical, and ethical considerations, with the aim of

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strengthening educational quality and promoting more dynamic and meaningful interaction in the classroom [18, 19]. Consequently, AI should not be conceived merely as an auxiliary tool; rather, it functions as a transformative agent within the educational ecosystem, oriented toward the comprehensive strengthening of the formative process in higher education [20].

As technological tools become increasingly integrated into classrooms, the need arises to understand their impact on the teaching–learning process. Despite significant technological advances and their implementation in the educational sector, challenges of various kinds persist, requiring reflection on the effectiveness of these tools in supporting learning [21], particularly as automation and data intelligence are giving rise to new professional roles that demand specialized skills and adaptable mindsets [22]. In response to this new reality, the educational sector is compelled to adopt a proactive approach that ensures institutional adaptation to technological change. This demands the design and implementation of innovative strategies that involve both faculty and students, enabling them to develop digital and cognitive competencies aligned with current environmental demands [23].

Despite the growing academic interest in the integration of AI in higher education, the literature reveals significant research gaps. In particular, while studies have focused on the benefits of AI in terms of learning outcomes and pedagogical efficiency, there is limited empirical evidence on the role of pedagogical strategies in fostering autonomous learning and cognitive processes among university students. The existing literature has explored the role of AI in education across various contexts; however, there is a notable lack of quantitative research focused on specific applications of AI in higher education and their impact on academic performance [24]. This lack of empirical studies that integrate technology, learning, and learner autonomy constrains the understanding of AI within educational processes, thereby highlighting the need for further research that explicitly addresses this relationship. In this regard, the present study aims to determine the relationship between communication strategies employed by students in the university context and their academic development. Moreover, it seeks to generate scientific evidence that contributes to improving instructional processes, reinforcing the importance of communication strategies as a transversal axis of learning.

II. Literature Review

A. Intelligent Pedagogical Strategies

Pedagogical strategies are action plans designed to manage the organization and sequencing of content, define learning activities, and determine methods that best support teaching processes [25, 26]. The application of intelligent strategies has been shown to enhance the effectiveness of flipped classrooms by optimizing students' learning experiences and outcomes while reducing teachers' workload [27]. Consequently, adaptive learning systems have been developed to ensure that students receive pedagogically relevant content aligned with their learning styles, thereby promoting more inclusive and effective learning strategies and fostering academic success [28]. These environments cultivate digital, interpretive, productive, and reproductive competencies that stimulate students' potential through the use of digital resources—such as hyperlinks, interactive tools, and intelligent correction systems—which streamline learning processes [29]. It is important to emphasize that the use of artificial intelligence in academic, professional, and social domains should be understood as an assistant that guides, clarifies ideas, and helps solve problems. The various applications of AI arise from the characteristics of the pedagogical strategies selected by teachers and students, with the aim of strengthening the educational process and developing the competencies and skills required for authentic and meaningful learning [30]. Moreover, assessment systems that incorporate artificial intelligence represent a major innovation in education, as they can adapt to the individual characteristics of each learner [31]. Through advanced algorithms and machine-learning techniques, student performance can be analyzed and interpreted objectively and efficiently, allowing AI to recommend relevant learning resources—such as articles, videos, and books—and to respond to students' inquiries [32, 33].

B. Digital Innovation in Education

Artificial Intelligence (AI) is a machine-based intelligent system that encompasses learning, communication, information processing, and inductive reasoning, enabling it to perform functions traditionally associated with human cognition [34, 35]. It includes a wide range of tools and machine-learning algorithms capable of working with large text corpora to extract and process information, detect patterns, make predictions, and optimize educational processes [36]. These methodologies allow students to develop essential skills—such as self-assessment and autonomy—through experimentation and collaborative learning [37]. Consequently, integrating intelligent technologies into learning environments creates new opportunities by serving as a support tool for investigating and understanding complex concepts, while promoting active and collaborative engagement among educators and students to achieve academic goals. Such integration fosters critical and reflective scenarios that enrich the teaching–learning process [38, 39].

Digital innovation complements education by accelerating the achievement of learning objectives, increasing accessibility, and advancing inclusion in higher education. Through the promotion of interdisciplinary dialogue and knowledge exchange, institutions can leverage collective expertise to build inclusive, ethical, and sustainable AI-driven educational systems [40]. From this perspective, AI emerges as a strategic element that helps universities fulfill their mission [41]. In this regard, AI-based chatbots provide students with dynamic and interactive learning experiences [23]. The most widely used tool is ChatGPT, an AI language model that employs advanced neural-network techniques to emulate certain functions of the human brain and generate coherent responses to user queries or prompts. This system belongs to the GPT-3.5 family, recognized as one of the most innovative and powerful in the field of artificial intelligence, capable of processing and understanding natural language as well as adapting to students' learning rhythms. It is used as a tool for lesson preparation, feedback delivery, student assessment, and the creation of digital and interactive educational resources, continually improving its task-optimization capabilities over time [42–47]

ChatGPT is a chatbot that uses the Generative Pre-trained Transformer (GPT) architecture and AI techniques to generate coherent responses within educational contexts, where it exhibits broad and diverse potential ranging from writing articles, stories, poems, and essays [44, 48] to emulating linguistic interactions and dialogic patterns [49]. It can summarize information, expand content, translate texts, make predictions, create scripts, generate programming code, produce speeches, answer questions, and perform tasks requiring various levels of reasoning—such as deciphering words, using vocabulary in context, or completing arithmetic operations [46]. These capabilities underscore its value in optimizing learning processes and demonstrate its utility in educational settings. Recent studies highlight the role of AI chatbots—often referred to as conversational robots, agents, or personalized assistants—which "converse through text" with human users [50].

Chatbots such as Bard, developed by Google AI, Ada, Gemini, and Copilot use text-generation capabilities to create a variety of creative content and provide personalized tutoring and feedback to students [51, 52]. These tools not only enrich learning but also help students advance in the construction of their knowledge structures, enabling them to acquire foundational concepts autonomously and fostering deeper reflection and understanding [53]. However, it is essential to maintain critical awareness of their pedagogical implications to ensure the effective and ethical integration of artificial intelligence in higher education. This requires thoughtful decision-making involving both students and instructors, guided by clear educational objectives, shared values, and an appropriate understanding of contextual factors [54].

C. Integration of Artificial Intelligence in the Learning of University Students in Peru

The process of digitalization is advancing in higher education worldwide, although not in an equitable manner. North America and Europe serve as leading references; in comparison, Latin America exhibits lower and more heterogeneous levels of connectivity, greater reliance on mobile access, less consolidated AI governance frameworks, and more limited availability of devices in educational environments [55].

In the education system of the Kingdom of Bahrain, it has been reported that higher education institutions are implementing digital transformation and facilitating smart education [56]. In China, one of the main advantages of smart classrooms is their high level of interactivity, which enables the creation of diverse types of interactions among teachers, students, and learning materials, resulting in improved student learning effectiveness [57]. Likewise, in the United Arab Emirates, the tool ChatGPT functions as a generative AI chatbot that promotes autonomy during learning activities, consistent with the broader philosophy of self-directed learning [58]. In the United States, federal and state policies emphasize the integration of technology in education with the aim of improving student performance [59].

Within this context, five cutting-edge strategies have been proposed: active learning, experiential learning, technology-assisted learning, flipped classroom–based learning, and problem-solving and critical thinking–based learning, implemented through Smart Pedagogical Learning and Assessment Methodology (SPLAM) integrated with the Outcome-Based Education (OBE) framework, resulting in the SPLAM–OBE model. This design complies with the requirements of the OBE framework established by the National Board of Accreditation in India and with the standards of major international program accreditation agencies, such as the Institution of Engineering and Technology in the United Kingdom and the Accreditation Board for Engineering and Technology in the United States [60]. These developments reflect universities' efforts to remain at the forefront by adapting to emerging trends and preparing future professionals for an increasingly complex and dynamic environment [61].

Latin American institutions operate under AI-related constraints that affect access, quality of use, and pedagogical alignment [62], due to challenges such as the lack of clear ethical frameworks for the implementation of AI in Latin American universities. In Peru, the university system operates within a developing economic context in which the adoption of educational technologies follows patterns different from those observed in developed countries. The higher education landscape is characterized by a marked disparity in resources between public and private universities, generating significant gaps in technological infrastructure and capacity for pedagogical innovation [63]. Consequently, the integration of AI in higher education remains at an incipient stage of development due to digital divides [64].

In this regard, researchers highlight the practical benefits, the social context, and the role of trust in the adoption of AI in Peruvian higher education [65]. Accordingly, faculty members demonstrate a positive attitude toward adopting AI for content creation, assessment, feedback, and research [66]. For example, Vásquez *et al*. [67] conducted a study on the AI tool Consensus, designed to enable students to locate and download reliable research articles from various scientific journals. This tool is expected to support the teaching–learning process and enhance the digital knowledge of higher education students in Peru and across different Latin American countries.

Within this context of Peruvian higher education, AI has proven to be fundamental for the successful adoption of emerging technologies and for improving autonomous learning [63]. Therefore, the incorporation of AI in higher education has marked the beginning of a new stage in teaching–learning processes, transforming the way teachers and students access knowledge. This technology has become an effective tool for increasing efficiency, adapting education to individual needs, and expanding its accessibility to all university students [68].

D. Self-directed Learning

Self-directed learning refers to students' ability to self-regulate their learning processes, taking into account motor, social, affective, and cognitive competencies [69, 70]. The autonomy students develop helps them consciously guide, control, regulate, and evaluate their own learning in order to achieve both academic and professional goals [71]. The concepts of academic autonomy and self-directed learning are frequently used by instructors in higher education, recognizing that self-regulation is not merely an inherited process but is also acquired through pedagogical mediation provided by the teacher. It is therefore essential to analyze these constructs in their interdependence to highlight their significance within collaborative learning processes, with the aim of encouraging educators to help students develop the skills necessary to achieve their goals and objectives [72]. Consequently, fostering autonomy and self-regulation supports the development of metacognitive skills such as introspection and personal control over one's learning [73].

AI has the potential to enhance university students' learning by providing real-time feedback and revolutionizing teaching methodologies in the long term [74]. Therefore, AI supports learning by identifying students' needs, interests, and competencies that can be developed autonomously, as it guides personalized learning pathways and facilitates decision-making through continuous feedback [75] via intelligent tutoring tools, automated assessment, and the generation of educational materials, thereby reducing the time burden on both teachers and students through a dynamic approach [76].

Self-regulatory processes enable students to direct, monitor, and regulate their knowledge within the environments in which they operate, allowing them to set their own learning goals [69]. In this process, students self-regulate their learning through three stages: setting learning goals, monitoring their progress through metacognitive strategies, and evaluating outcomes to improve their knowledge [77]. Within this framework, the implementation of effective learning strategies promotes knowledge acquisition and strengthens metacognitive processes [78]. To achieve this, it is necessary to properly structure strategies that facilitate students' self-regulation and academic performance [79]. Likewise, the personal experiences students accumulate throughout their academic journey are linked to the regulation of their learning and involve cognitive and behavioral components that support strong academic development. These experiences enhance their ability to recognize and modify their skills, adapt to contextual demands, and ensure success in fulfilling their learning goals [80, 81].

In this regard, learning strategies such as self-regulation are essential components of the educational process, as they enable students to manage their cognitive and emotional resources in a balanced way throughout their academic trajectory [82]. Numerous studies have demonstrated that applying self-regulatory techniques—such as planning activities, engaging in continuous self-evaluation, and reviewing one's own performance—significantly increases the likelihood of achieving higher academic performance [83]. Their relevance lies in the fact that they foster a stronger sense of self-efficacy, more conscious control over learning processes, and greater adaptability when facing academic challenges, ultimately promoting students' active commitment to their goals [84].

Cognitive ability refers to the basic skills that support the acquisition and processing of new knowledge—skills that are crucial for learning and directly affect students' performance [85, 86]. Cognitive variables involve active and constructive processes through which students guide their behavior with the goal of fulfilling their objectives [87]. In this sense, affective engagement enables students to anticipate or evaluate their expected performance across future academic tasks [88]. Conversely, if cognitive ability is low or impaired—such as through lack of motivation—important information may be lost during processing, negatively affecting performance. This often results in reduced production of meaningful information, poorer academic outcomes, and decreased interest in a course or higher education system. Therefore, cognitive and psychological factors play a decisive role in enhancing academic performance [89–91].

Students' cognitive capacity can be positively influenced through the use of tools such as ChatGPT. Its implementation supports the development of critical, creative, and reflective thinking by encouraging students to analyze, generate innovative ideas, and question information. These processes strengthen essential cognitive skills such as comprehension and problem solving. However, excessive, or inappropriate use raises concerns regarding its potential impact on students' cognitive abilities [92, 93].

Today, knowledge and technology play a central role in the university educational system, which must prioritize fostering the ability to "learn how to think" to stimulate greater brain activity and dynamic learning. This, in turn, enables reflection on one's own knowledge—how it is acquired, regulated, and evaluated—giving rise to metacognition [94]. Metacognition is a key element of learning that involves processes of falsification, comparison, and evidence-based judgment to assess specific situations [95, 96]. It allows individuals to acquire knowledge and control over their own thinking, guiding and regulating their learning process while considering the context in which they operate [97]. This process is closely linked to strategic learning and educational quality, enabling students to develop skills that strengthen both academic and personal activities. Within this process, teachers play an essential role, helping students become active participants capable of directing and self-regulating their own learning, thus promoting autonomy and contributing positively to their academic development and performance [98, 99]. Metacognition also involves the inclusion of awareness as a regulatory mechanism, allowing students to control their learning through the tools and strategies they apply, ultimately promoting successful, autonomous, and critically reflective learning [100, 101]. Through reflective practice, students identify their strengths and weaknesses and use them to plan their cognition, effectively managing and regulating meaningful learning and working toward greater independence. This includes the use of metacognitive strategies that enhance their adaptability across diverse learning environments [102, 103]. Therefore, the relationship between metacognition and motivation is fundamental to achieving success, as students who possess greater awareness of their mental processes tend to use more effective learning strategies, display stronger performance, and demonstrate higher levels of planning, monitoring, and evaluation of their own learning. This relationship is essential across all educational levels [104–106].

III. Materials and Methods

The study adopted a non-experimental, cross-sectional design with a quantitative approach. In the first phase, an exhaustive review of the literature was conducted in order to construct a theoretical framework on Artificial Intelligence (AI)–based methodological strategies and their relationship with the development of autonomous learning in higher education students, identifying relevant conceptual gaps and areas of research interest. In the second phase, an online survey was administered to a non-probabilistic convenience sample consisting of 383 university students enrolled from the first to the tenth academic cycle, belonging to diverse academic fields such as social sciences, economic sciences, and engineering. Data collection was carried out between April and July using the Google Forms platform.

The instrument was designed by the principal researcher and validated through expert judgment (n = 3), ensuring content validity. The questionnaire was structured into three sections: (1) sociodemographic data, including age, sex, marital status, and academic cycle; (2) AI methodological strategies, specifically virtual assistants; and (3) autonomous learning, encompassing cognitive learning capacity, affective–motivational participation, self-regulation processes, and metacognitive processes. The data were systematized in Microsoft Excel and analyzed using SmartPLS v4 software. Instrument reliability was assessed using Cronbach's alpha coefficient, considering values ≥ 0.70. According to [107], Cronbach's alpha (α) is characterized as a measure of internal consistency used to estimate the reliability of the proposed items and to determine whether they are representative for the research. These results indicate that the items are correlated and that the instrument is reliable, since values ≥ 0.70 are considered acceptable and reflect a higher degree of correlation among items [108, 109] (Table 1).

To analyze the relationships among the latent constructs, Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed, a technique suitable for complex models with multiple variables and strong predictive capacity. The proposed framework integrates constructs with multiple indicators; therefore, PLS-SEM was selected due to its efficiency in high-dimensional contexts and its lower requirements regarding data distribution and sample size [110]. The objective of the study was to predict and explain the variance of the dependent variables: AI Methodological Strategies (AIMS), Autonomous Learning (AL), and Academic Development (AD) (Fig. 1). The use of PLS-SEM ensures theoretical coherence and methodological appropriateness given the nature of the research problem [111], while providing robust predictive capability and efficient estimation of explained variance and the relationships among latent constructs [112].

A. *Ethical Approval and Informed Consent*

Prior to their participation, all individuals were fully informed about the study's nature, objectives, and how the data would be used. Informed consent was obtained, with participants explicitly assured that their involvement was entirely voluntary and that their responses would be used solely for academic research.

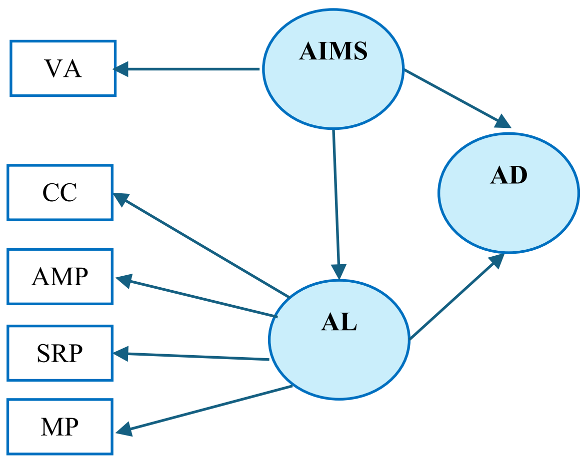
Table 1. Assessment of item reliability according to Cronbach's alpha coefficient

Índex	Reliability Level	Cronbach's Alpha Value
1	Excellent	0.81, 1.00
2	Very Good	0.61, 0.80
3	Good	0.41, 0.60
4	Fair	0.21, 0.40
5	Poor	0, 0.20

Note. Prepared by the author based on the criteria of [113].

The hypotheses proposed in the study were as follows:

- Autonomous Learning (AL) is related to Academic Development (AD).
- Virtual Assistants (VA) are related to Academic Development (AD).
- Virtual Assistants (VA) are related to AI Methodological Strategies (AIMS).
- AI Methodological Strategies (AIMS) are related to Academic Development (AD).
- Affective-Motivational Participation (AMP) is related to Autonomous Learning (AL).
- Affective-Motivational Participation (AMP) is related to Academic Development (AD).
- Self-Regulation Processes (SRP) are related to Autonomous Learning (AL).
- Self-Regulation Processes (SRP) are related to Academic Development (AD).
- Metacognitive Processes (MP) are related to Autonomous Learning (AL).
- Metacognitive Processes (MP) are related to Academic Development (AD).



Note. AI Methodological Strategies (AIMS), Autonomous Learning (AL), Academic Development (AD), Virtual Assistants (VA), Cognitive Capacity (CC), Affective-Motivational Participation (AMP), Self-Regulation Processes (SRP), and Metacognitive Processes (MP).

Fig. 1. Conceptual model.

IV. Result and Discussion

A. *Result*

1) *Descriptive analysis*

Regarding the analysis of students' sex (Table 2), 56% are female and 44% are male. With respect to age, 89% of the students are between 18 and 24 years old, while 7% fall within the 25–34 age range, and only 3% are between 35 and

44 years old. Concerning marital status, 96% of the students are single and 4% are married. Finally, in terms of academic term, 31% of the participants are in the third term, followed by 23% in the first term and 15% in the second term.

Table 2. Descriptive analysis of the students

Variable		n	f
Sex	Female	216	56%
	Male	167	44%
	Total	383	100%
Age	18–24 years	339	89%
	25–34 years	28	7%
	35–44 years	13	3%
	45 years and over	3	1%
	Total	383	100%
Marital Status	Married	17	4%
	Single	366	96%
	Total	383	100%
Academic Term	I	88	23%
	II	58	15%
	III	117	31%
	IV	39	10%
	IX	8	2%
	V	27	7%
	VI	17	4%
	VII	12	3%
	VIII	12	3%
	X	5	1%
	Total	383	100%

In Table 3, the individual item reliability for the SEM analysis is presented, with particular attention given to construct validity, reliability, and hypothesis testing. For the analysis of item reliability, all loadings are above 0.707 [114]. Furthermore, the Variance Inflation Factor (VIF) was used to detect possible multicollinearity among the variables. A variable is considered to exhibit high collinearity when the value exceeds 10; however, in this study, all VIF values fall below the threshold of 10 [115].

Table 3. Individual item reliability for the measurement model

Latent Variable	Outer Loading	VIF	AVE	VIF
VA_1	0.89	1.59	0.80	1.00
VA_2	0.90	1.59		
AMP_1	0.89	1.48	0.79	1.628
AMP_2	0.89	1.48		
SRP_1	0.83	1.65	0.69	1.891
SRP_2	0.85	1.72		
SRP_3	0.81	1.48		
MP_1	0.79	1.40	0.69	1.694
MP_2	0.86	1.86		
MP_3	0.83	1.70		

2) *Inferential analysis*

Regarding the internal consistency of the measurement scales, the composite reliabilities of the constructs exceed 0.7, as shown in Table 4. Therefore, it can be affirmed that the items or manifest variables are indeed relevant to the model, as reflected in the following values: VA = 0.892, AMP = 0.880, SRP = 0.869, and MP = 0.867.

The Average Variance Extracted (AVE) coefficient represents the proportion of variance in the construct that can be explained by its indicators. It is verified that this coefficient is greater than 0.5 for all the constructs, as shown in Table 5; therefore, we can affirm that there is convergent validity for each of the latent variables [116].

Table 4. Composite reliability

Construct	Cronbach's Alpha	Composite Reliability
Virtual Assistants (VA)	0.757	0.892
Affective–Motivational Participation (AMP)	0.727	0.880
Self-Regulation Processes (SRP)	0.775	0.869
Metacognitive Processes (MP)	0.769	0.867

Table 5. Average variance extracted

Construct	Average Variance Extracted (AVE)
Virtual Assistants (VA)	0.80
Affective-Motivational Participation (AMP)	0.79
Self-Regulation Processes (SRP)	0.69
Metacognitive Processes (MP)	0.69

Discriminant validity analysis refers to the extent to which a construct is empirically distinct from others; establishing it involves demonstrating that the construct is unique and captures dimensions of the phenomenon not represented by other constructs in the model. In this study, the Fornell–Larcker criterion was used [116], where Table 6 shows that all constructs achieve discriminant validity following the Fornell–Larcker criterion, with the diagonal displaying the square root of the AVE for each construct; therefore, all constructs measure different aspects.

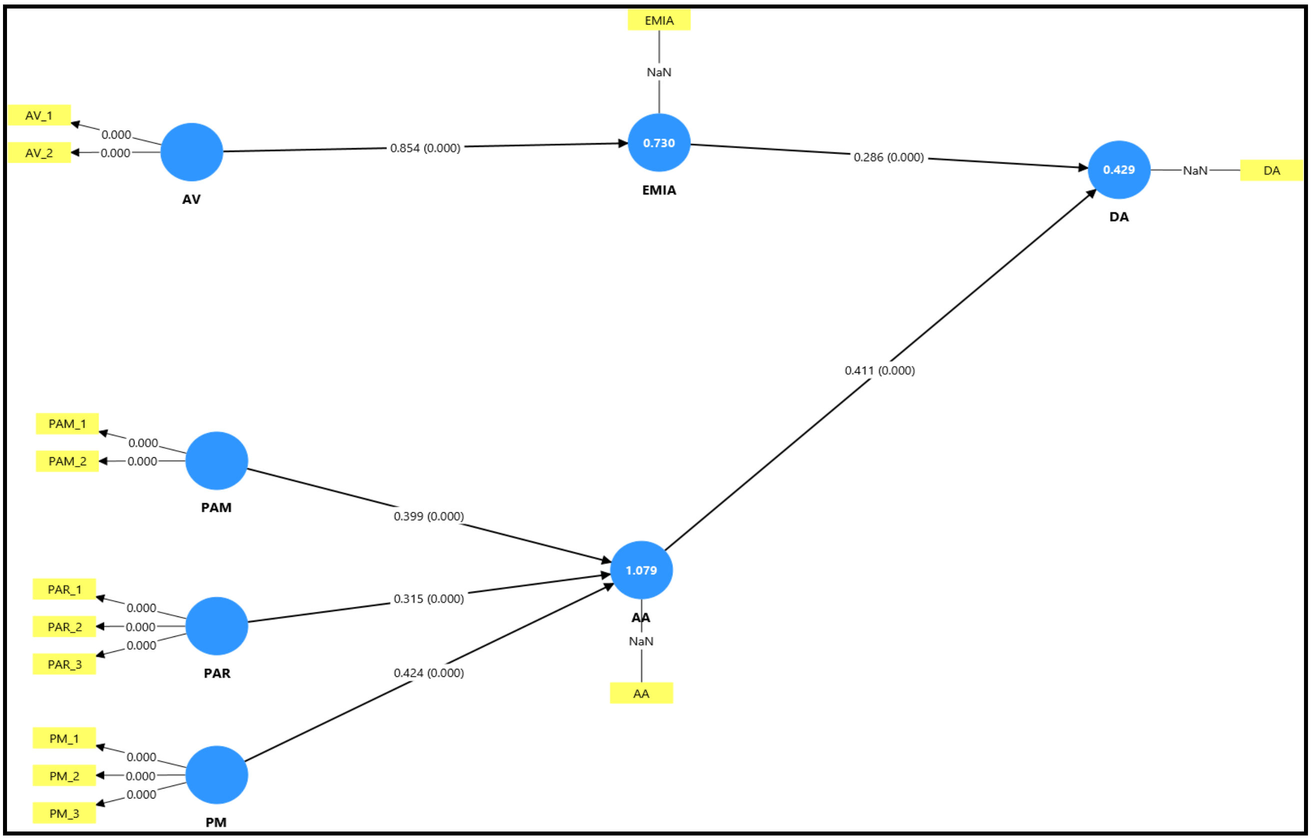
For the analysis of the structural model and hypothesis testing, Table 7 shows that AA is positively related to AD ($\beta = 0.411$, $t = 6.50$, $p < 0.05$). Likewise, VA is positively related to AD ($\beta = 0.212$, $t = 4.259$, $p < 0.05$), and VA is also positively related to AIMS ($\beta = 0.744$, $t = 26.83$, $p < 0.05$). AIMS is positively related to AD ($\beta = 0.286$, $t = 4.49$, $p < 0.05$). Additionally, AMP is positively related to AA ($\beta = 0.363$, $t = 18.9$, $p < 0.05$), and AMP is positively related to AD ($\beta = 0.149$, $t = 6.210$, $p < 0.05$). SRP is positively related to AA ($\beta = 0.383$, $t = 22.5$, $p < 0.05$), and SRP is positively related to AD ($\beta = 0.157$, $t = 6.291$, $p < 0.05$). Finally, MP is positively related to AA ($\beta = 0.411$, $t = 19.96$, $p < 0.05$), and MP is positively related to AD ($\beta = 0.169$, $t = 6.41$, $p < 0.05$) (Fig. 2).

Table 6. Discriminant validity

Construct	AA	VA	AD	AIMS	AMP	SRP	MP
AA	1.000	….....	….....	….....	….....	….....	….....
VA	0.535	0.897	….....	….....	….....	….....	….....
AD	0.628	0.483	1.000	….....	….....	….....	….....
AIMS	0.760	0.744	0.598	1.000	….....	….....	….....
AMP	0.801	0.455	0.525	0.654	0.886	….....	….....
SRP	0.846	0.372	0.423	0.576	0.587	0.830	….....
MP	0.832	0.412	0.524	0.588	0.518	0.608	0.828

Table 7. Hypothesis testing

Hypothesis	Effect	Path Coefficients	t-value	p-value	Supported?
Autonomous Learning (AL) → Academic Development (AD)	+	0.411	6.506	0.000	Yes
Virtual Assistants (VA) → Academic Development (AD)	+	0.212	4.259	0.000	Yes
Virtual Assistants (VA) → AI Methodological Strategies (AIMS)	+	0.744	26.833	0.000	Yes
AI Methodological Strategies (AIMS) → Academic Development (AD)	+	0.286	4.499	0.000	Yes
Affective-Motivational Participation (AMP) → Autonomous Learning (AL)	+	0.363	18.921	0.000	Yes
Affective-Motivational Participation (AMP) → Academic Development (AD)	+	0.149	6.210	0.000	Yes
Self-Regulation Processes (SRP) → Autonomous Learning (AL)	+	0.383	22.527	0.000	Yes
Self-Regulation Processes (SRP) → Academic Development (AD)	+	0.157	6.291	0.000	Yes
Metacognitive Processes (MP) → Autonomous Learning (AL)	+	0.411	19.966	0.000	Yes
Metacognitive Processes (MP) → Academic Development (AD)	+	0.169	6.413	0.000	Yes



Note. Abbreviations in the figure have been translated for clarity: PAM = AMP, PAR = SRP, PM = MP, DA = AD, EMIA = AIMS, AV = VA.

Fig. 2. Structural model.

B. Discussion

The study provides empirical evidence on the relationship between smart pedagogical strategies and the development of autonomous learning among university students. The findings indicate that the pedagogically grounded integration of AI strengthens cognitive processes such as self-regulation. In line with [117], AI is argued to promote autonomous learning by enabling students to work independently and at their own pace, with technologies such as ChatGPT serving as useful tools for students who struggle with specific concepts or seek rapid review and reinforcement.

The findings reveal that AI-based methodological strategies have a significant and positive effect on the academic development of higher education students ($\beta = 0.286$, $t = 4.49$, $p < 0.05$). This result indicates that the integration of intelligent technologies promotes more personalized and efficient teaching processes, aligning with [118], who argues that AI transforms education by enabling personalized learning and enhancing teaching practices through the automation of academic tasks. Likewise, the results show that the use of virtual assistants is strongly related to AI methodological strategies ($\beta = 0.744$) and to academic development ($\beta = 0.212$). These findings reinforce the claims of [23], who highlight how virtual assistants increase motivation by offering adaptive and personalized resources that foster autonomous learning. The study conducted by [75] contributes to the literature by indicating that university students use AI chatbots such as ChatGPT to complete written assignments, with 60% using the program for more than half of their tasks. Likewise, the findings of the study by [66] suggest that Peruvian university students who have greater confidence in their ability to learn and use AI are more likely to appropriate these technologies. The high correlation regarding AI use ($\beta = 0.711$) found in the study by Arbulú *et al*. [119] refers to chatbot capabilities, response quality, and user interface design.

Creativity, as a phenomenological construct, is not immune to the effects of AI [118]. The emergence of artificial intelligence technologies has introduced new challenges and opportunities, prompting critical reflection on their implications for creativity and learning [120]. Consequently, significant gaps remain in the understanding of how students interact with these tools in authentic learning contexts. Nevertheless, it is crucial to determine not only their potential to foster creativity, but also the risks they may pose to originality, autonomy, and diversity of thought. Accordingly, studies suggest that students are currently situated within a new era of "assisted creativity," in which AI is not an independent creator [121], but rather a collaborative creative agent with fluid adaptive capabilities [122]. From this perspective, AI functions as a mediating tool that expands students' cognitive exploration.

The analysis of self-regulation and metacognitive processes shows significant positive effects on autonomous learning (β = 0.383 and β = 0.411, respectively) and on academic development (β = 0.157 and β = 0.169). These results are consistent with [83], who argues that self-regulation involves setting goals, monitoring progress, and evaluating results—key actions that strengthen self-management and autonomy. Similarly, [55] affirm that metacognitive processes enhance comprehension, monitoring, and evaluation of one's own learning, which directly impacts academic development [123]. These outcomes also support [73], who emphasizes that motivation enhances the effectiveness of metacognitive strategies, promoting autonomy and students' readiness for independent learning. Furthermore, the findings show that affective-motivational participation is significantly related to autonomous learning (β = 0.363) and academic development (β = 0.149). This reinforces the idea that motivation is an essential factor in the learning process, in line with [88]. Motivation acts as a catalyst that strengthens self-regulation and self-confidence, promoting active engagement among university students. This dimension also aligns with [124, 125], who state that AI-driven personalized learning supports students' individual needs, strengthening the interaction between the emotional and cognitive components of learning.

Regarding students' perceptions, the study revealed high average ratings for virtual assistance and system flexibility. These findings are consistent with [9], who argue that the combination of AI tools and knowledge is transforming the educational landscape by promoting autonomous learning supported by intelligent and personalized methodological strategies. Likewise, Alabool [126] states that AI must be employed from an ethical perspective, and Martínez-Rolán, Cabezuelo, and Oliveira [127] emphasize the need to identify the ethical implications and biases inherent in AI systems, reinforcing the importance of a responsible implementation of these digital tools.

One of the main challenges in the use of artificial intelligence in higher education lies in students' limited ability to critically evaluate the information generated by these algorithms. Research by Nontsikelelo and H. Nomasomi [128] argue that one of the primary concerns regarding the disproportionate use of AI is its potential to diminish critical thinking and analytical skills; by unreflectively accepting AI-generated interpretations without questioning them, students may constrain their analytical abilities and critical reasoning. To mitigate this limitation, it is essential to design pedagogical strategies aimed at strengthening metacognitive skills and self-regulated learning through more inclusive, flexible, and personalized learning systems [129]. Moreover, Agüero *et al*. [130] emphasize that the use of technology in educational contexts should not be merely instrumental, but should facilitate collective processes of knowledge construction, promoting contextualized, participatory, and transformative learning. These perspectives converge on the need to integrate an ethical, inclusive, and critical approach to the adoption of technological resources in education, maintaining a balance between innovation, humanism, and technology. Therefore, continuous monitoring and validation of the performance and outcomes of AI applications are required, as well as timely intervention when necessary to correct or enhance their effectiveness [131].

Another finding shows that autonomous learning (β = 0.411) has a direct effect on academic development, demonstrating that self-regulation, planning, and metacognitive processes are aimed at academic performance. This aligns with the results reported by Puya *et al*. [72], who highlight that autonomy enables students to guide, control, and regulate their own learning. Similarly, Theobald [82] provides evidence that the application of self-regulatory techniques and continuous self-assessment significantly increases self-efficacy and academic engagement. In this context, the results support the use of educational chatbots as mediating tools for autonomous learning. This finding contributes to the work of [33], who emphasize that AI systems are capable of analyzing university students' performance through advanced algorithms and can likewise provide adaptive feedback, enhancing learning efficiency. Martínez [42] notes that models such as ChatGPT, based on transformer neural networks, serve as a support resource similar to human reasoning and improve the quality of the educational process by generating coherent responses. Furthermore, [44] highlight the ability of these systems to reproduce complex linguistic interactions, facilitating university students' comprehension and text production. Additionally, the use of tools such as Bard, Ada, Gemini, and Copilot broadens the possibilities for tutoring and dynamic feedback [51]. In this regard, the study's findings confirm that AI-based methodological strategies strengthen the relationship between autonomous learning and academic development, fostering adaptive education. However, it is essential to evaluate the potential overdependence on automated systems. As points out [30], AI should be conceived as a guiding assistant rather than a substitute for human reasoning.

The development of metacognitive skills and autonomous learning is closely linked to the sociocultural context in which students operate. According to Condori *et al.* [132], autonomous learning is defined as a multimodal process that integrates cognitive and socio-affective dimensions (such as self-regulation, metacognition, and critical reflection), grounded in constructivist and sociocultural theoretical foundations. Likewise, Zheng, Hu, and Wang [133] indicate that cognitive factors—such as perceived usefulness, metacognitive capacity, and self-efficacy—indirectly influence students' behavior through social interactions. From a constructivist perspective, learning is understood as a process that promotes social interaction and cultural context in cognitive development, which aligns with the capacity of AI to foster learner autonomy [134]. In this study, smart pedagogical strategies are conceptualized as mediators of learning. Nevertheless, it is acknowledged that the methodological design does not allow for absolute control of sociocultural variables, which constitutes a limitation of the study.

Artificial intelligence in higher education raises ethical challenges that require systematic attention. The primary risks include student privacy, the protection of personal data, intellectual property rights, algorithmic bias, and excessive dependence on AI tools [135]. Therefore, it is essential for educational institutions to adopt clear policies on data governance, algorithmic transparency, and responsible technology use in order to cultivate students' ethical and critical competencies, while recognizing both the advantages and limitations of AI applications.

V. Conclusion

The study confirms that autonomous learning is an essential mediator between artificial intelligence–based pedagogical strategies and academic performance in higher education. The findings demonstrate that self-regulation, metacognition, and affective motivation are determinant variables that strengthen students' cognitive and emotional independence, fostering processes of reflection and continuous self-evaluation of their own learning. In this context, autonomy is not limited to task execution, but rather entails the development of essential digital and cognitive competencies for lifelong learning.

The findings suggest that universities should integrate artificial intelligence through educational policies that prioritize its pedagogical and formative use, avoiding purely instrumental approaches. For educators, it is recommended to design learning experiences that promote the critical and reflective use of AI tools such as ChatGPT, Ada, Bard, Gemini, or Copilot, oriented toward learning regulation, information quality assessment, and the autonomous construction of knowledge. Likewise, educational policies should promote regulatory frameworks that encourage teacher training in digital, metacognitive, and ethical competencies, ensuring the responsible and equitable adoption of AI within the university system.

The incorporation of artificial intelligence into higher education represents a paradigmatic shift that redefines educational methodologies, the role of the teacher, and learning dynamics. When integrated ethically and critically, AI contributes to a more dynamic and inclusive higher education by fostering students' autonomous development. Achieving this requires strengthening faculty development in digital competencies and promoting an academic culture of responsible innovation, as AI should be conceived as a guiding instrument capable of enhancing creativity and critical reflection within the framework of ethical and autonomous learning.

From a theoretical perspective, the study provides empirical evidence that consolidates autonomous learning as a key mediating construct between artificial intelligence–based pedagogical strategies and academic performance, expanding models of self-regulated learning by integrating cognitive and metacognitive dimensions within digitized educational environments. Likewise, the findings indicate that technologies act as mediators of cognitive learning in Peruvian higher education. From a practical standpoint, the results offer guidance for pedagogical innovation and the formulation of institutional policies, highlighting the need to integrate artificial intelligence in an ethical and critical manner, thereby contributing to educational quality and the reduction of gaps within the country's university system.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

P.E.L.-V. conducted the research; Y.J.R.A. and L.V.A.L. analyzed the data; P.E.L.-V. drafted the article. All authors collaborated in the analysis of the data, interpretation of the results, and preparation of the manuscript. Each author critically reviewed the manuscript for important intellectual content and approved the final version for publication.

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