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Factores determinantes en la adopción de inteligencia artificial en la educación superior dominicana

Determining factors in the adoption of Artificial Intelligence in Dominican higher education

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Abstract

Given the growing importance of this technology and the scarcity of studies in this context, this research examines the determining factors in the effective adoption of Artificial Intelligence (AI) in Dominican higher education. Using a quantitative approach, a sample of 101 university professors was analyzed through partial least squares structural equation modeling (PLS-SEM). The results reveal that teachers' attitudes toward AI and institutional support are the most significant predictors of effective adoption. Digital skills showed a significant indirect effect through attitudes, while technological infrastructure had minimal impact. The findings suggest that strategies to promote AI adoption should prioritize the development of positive attitudes among teachers and the strengthening of institutional support, beyond the mere provision of technology. The study contributes to the understanding of AI adoption in specific higher education contexts and provides a basis for future comparative research.

Keywords: artificial intelligence, higher education, innovation, attitudes, technology, AI ethics, digital competencies.

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Introduction

Higher education has undergone a profound transformation in recent decades due to the technological revolution, which has redefined teaching-learning processes and is demanding new competencies from both teachers and students (Cladis, 2020). In this context, Artificial Intelligence (AI) emerges as a technology with great potential to further revolutionize the educational landscape by offering possibilities for personalization, automation, and improved educational efficiency (Zawacki-Richter et al., 2019; Silva et al., 2024).

In the Dominican Republic, the integration of advanced technologies such as AI into higher education is still in a preliminary stage. Recent studies have highlighted the need to strengthen technological infrastructure and teachers' digital competencies in Dominican universities (Pérez et al., 2022). In this regard, the research conducted by Rodríguez and Gómez (2023) identified a significant gap between educational policies that promote technological innovation and the reality of university classrooms, highlighting the need to examine the factors that facilitate or hinder the adoption of new technologies in the Dominican higher education system.

Although reflections on the ethical implications of AI in learning assessment (VanderLinde & Mera, 2024) and its potential educational applications (Medina, 2024) have begun to emerge in the Dominican context, there is still a notable gap in the understanding of the factors that influence its effective adoption. International literature has identified various factors that influence the adoption of advanced educational technologies, including teachers' digital competencies, their attitudes toward innovation, institutional support, and the available technological infrastructure (Rogers, 2003; Johnson et al., 2021). However, these factors may interact differently across diverse cultural and socioeconomic contexts.

Given this issue, there is a need to systematically investigate the factors that influence the effective adoption of AI in Dominican universities. Consequently, this research is guided by the following main question: What are the determining factors in the effective adoption of Artificial Intelligence in Dominican higher education?

The main objective of this study is to analyze the factors that influence the effective adoption of Artificial Intelligence in higher education in the Dominican Republic, with special attention to the interaction between teachers' digital competencies, attitudes toward AI, institutional support, and the available technological infrastructure.

This study is highly relevant for higher education institutions in the Dominican Republic, as it will contribute to a more successful implementation of AI in the Dominican educational context. Furthermore, the results obtained may have broader implications for other developing countries seeking to integrate advanced technologies into their educational systems.

Having explained the above, the content of this study is structured as follows: first, a review of the relevant literature on AI in higher education and the factors influencing its adoption is presented. Next, the methodology employed is detailed, including the research design, data

collection, and statistical analysis. Subsequently, the results obtained are presented, followed by a discussion interpreting these findings within the context of the existing literature. Finally, the study concludes with the practical and theoretical implications of the research, as well as suggestions for future studies.

Theoretical Framework

Artificial Intelligence (AI) is conceptualized as a set of technological systems, including software and potentially hardware, created by humans to address complex tasks. These systems operate in both digital and physical environments through a sequential process that includes the perception and acquisition of environmental data, the processing and interpretation of both structured and unstructured information, the analysis and reasoning of the derived knowledge, and finally, the selection and implementation of the most appropriate actions to achieve established objectives (European Commission, 2018).

Historically, the concept of AI emerged in the 1950s, but it has experienced accelerated development in recent decades due to advances in computational capacity and data availability. In the educational context, AI has multiple potential applications, ranging from intelligent tutoring systems to predictive analysis of student performance (Zawacki-Richter et al., 2019).

Indeed, the integration of Artificial Intelligence (AI) into higher education has experienced exponential growth in recent years, transforming teaching-learning processes and institutional management across diverse cultural and geographical contexts (Zawacki-Richter et al., 2019).

AI in higher education encompasses a wide range of applications. Rose Luckin and Mutlu Cukurova (2019) categorize these applications into three main areas: intelligent tutoring systems, learning analytics, and conversational agents. Intelligent tutoring systems, such as the one developed by Nye et al. (2018), use AI techniques to provide personalized instruction and adaptive feedback. Learning analytics, on the other hand, employs AI algorithms to process large amounts of educational data, thereby facilitating the early identification of at-risk students and the optimization of teaching strategies (Viberg et al., 2018).

Conversational agents or educational chatbots represent an emerging frontier in the application of AI in higher education. Rainer Winkler and Matthias Söllner (2018) developed a theoretical framework for the design of educational chatbots that emphasizes the importance of social presence and natural interaction. This framework, widely adopted in the development of virtual assistants for higher education, has demonstrated significant improvements in student participation and satisfaction.

Models for the Implementation and Acceptance of AI

The theoretical framework of Artificial Intelligence in Education (AIED), proposed by Wayne Holmes et al. (2022), provides a solid foundation for understanding how AI can enhance and personalize learning. This framework highlights three main components:

1. **The domain model:** represents the knowledge that must be learned. It includes the structure of educational content, the relationships between concepts, and the learning objectives.
2. **The student model:** captures the individual characteristics of the learner, including prior knowledge, learning style, motivation, and progress. This model is continuously updated as the student interacts with the system.
3. **The pedagogical model:** encompasses teaching strategies and decisions regarding how content is presented to the student. It adapts according to the student model and the domain model in order to optimize learning.

This AIED framework provides a conceptual structure for the design and implementation of AI systems in higher education, facilitating personalized learning and dynamic adaptation to students' individual needs. Complementing this approach, Nese Goksel and Aras Bozkurt (2019) propose a model for AI adoption in higher education that considers institutional, technological, and pedagogical factors. Their study is based on a systematic review of the existing literature on AI in higher education. The authors analyzed 146 articles published between 2007 and 2019 using a qualitative content analysis methodology.

The model proposed by Goksel and Bozkurt (2019) identifies three main dimensions influencing the adoption of AI in higher education:

1. **Institutional factors:** including leadership, organizational culture, and institutional policies.
2. **Technological factors:** encompassing infrastructure, accessibility, and the usability of AI technologies.
3. **Pedagogical factors:** referring to alignment with learning objectives, personalization, and the improvement of the educational experience.

The researchers emphasize the importance of aligning AI implementation with educational objectives and students' needs. However, the study does not provide specific quantitative data, as its conclusions are based on the qualitative analysis of the reviewed literature.

As can be observed, the implementation of AI in higher education is not without challenges. Ben Williamson and Rebecca Eynon (2020) warn about the risks of excessive "datafication" in education. In their critical analysis, they examine how AI and data analytics are reshaping higher education while also expressing concerns regarding student privacy, equity in access to technology, and the potential loss of teacher autonomy. The authors argue that increasing dependence on AI systems could lead to a reductionist view of learning, ignoring crucial but difficult-to-quantify aspects such as critical thinking and creativity.

This critical perspective has driven the development of ethical frameworks for AI implementation in education. Holmes et al. (2022) propose a comprehensive ethical framework based on a Delphi study involving 31 international experts in AI and education.

Their framework identifies six key ethical principles: 1) protection and data, 2) transparency and explainability, 3) equity and non-discrimination, 4) professional responsibility, 5) promotion of human values, and 6) technical robustness and security.

For each principle, the framework provides specific guidelines and examples of practical application. For instance, to address transparency, the authors suggest that educational institutions provide clear information on how AI algorithms are used in academic decision-making, while also ensuring that students can question and appeal AI-based decisions.

This framework has been adopted by several universities in Europe and North America as a basis for their AI implementation policies, demonstrating its practical relevance within the context of higher education.

The adoption of AI in higher education is a complex process influenced by multiple factors. The Technology Acceptance Model (TAM), developed by Fred Davis (1989), remains highly influential for understanding this process. The original TAM proposes that the intention to use a technology is primarily determined by two factors: perceived usefulness and perceived ease of use.

Recent research has expanded and contextualized this model for the AI era. For example, Ronny Scherer et al. (2019) conducted a meta-analysis of 114 studies using TAM in educational contexts, encompassing 45,714 participants. This study provided an updated synthesis of the factors influencing the adoption of educational technologies. The authors found that, in addition to perceived usefulness and ease of use, factors such as subjective norms ($\beta = 0.30$), facilitating conditions ($\beta = 0.38$), and technological self-efficacy ($\beta = 0.19$) also play a significant role in the acceptance of educational technologies.

Specifically, regarding AI in higher education, Pui-Lam Lai (2022) adapted TAM by including additional factors such as AI anxiety ($\beta = -0.18$) and the perceived educational benefits of AI ($\beta = 0.42$). This study, conducted with 387 university professors in China, found that the perception of educational benefits was the strongest predictor of the intention to use AI in teaching.

These adaptations of TAM provide a more comprehensive framework for understanding the adoption of AI in higher education by considering not only technological aspects but also psychological and contextual factors specific to the educational environment.

On the other hand, the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Viswanath Venkatesh et al. (2003) has recently been updated by Yogesh K. Dwivedi et al. (2019) to include AI-specific considerations. This expanded model incorporates factors such as technological anxiety, AI self-efficacy, and AI-related subjective norms, thereby providing a more comprehensive framework for understanding AI adoption in educational contexts.

Complementing these general models, Timothy Teo et al. (2021) propose the AI Acceptance Model in Education (AI-MEA), specifically focused on the factors influencing educators'

adoption of AI. This model incorporates variables such as the perceived pedagogical usefulness of AI, ethical concerns, and self-efficacy in AI use, thereby offering a more nuanced and contextualized perspective for the educational field.

Everett Rogers' Diffusion of Innovations Theory (2003) has also been applied to the context of AI in higher education. Huang et al. (2019) used this framework to examine how the perceived characteristics of AI—relative advantage, compatibility, complexity, observability, and trialability—influence its adoption by higher education institutions. Their findings emphasize the importance of clearly demonstrating the benefits of AI and providing opportunities for educators to experiment with these technologies gradually.

Finally, the sociotechnical model of AI adoption in education proposed by Neil Selwyn (2019) suggests that AI adoption should be understood as an interconnected social and technical process. This model emphasizes the importance of considering not only technological aspects but also the social, cultural, and organizational factors influencing AI adoption.

In this regard, Selwyn (2019) highlights how existing power structures, institutional cultures, and established pedagogical practices can either facilitate or inhibit the adoption of AI in higher education.

When comparing the various models of AI adoption in higher education, an evolution can be observed from general frameworks such as TAM and UTAUT toward more specific and contextualized models. The meta-analysis conducted by Scherer et al. (2019) provides the strongest evidence supporting an extended version of TAM in educational contexts. This study demonstrates the importance of factors such as subjective norms and facilitating conditions beyond perceived usefulness and ease of use.

In contrast, the AI-MEA proposed by Teo et al. (2021), although more specific to AI, has a more limited empirical foundation. Likewise, Selwyn's (2019) sociotechnical model offers a more holistic perspective but lacks extensive empirical validation.

Taken together, these models suggest that AI adoption in higher education is a multifaceted process that requires consideration of technological, pedagogical, institutional, and sociocultural factors. Current evidence more strongly supports models that integrate both technological and contextual aspects, including the extended version of TAM and the updated UTAUT, although further research is needed to validate AI-specific models across diverse educational contexts.

Teachers' Digital Competencies

Teachers' digital competencies influence the adoption of AI in education. The DigCompEdu framework proposed by Christine Redecker (2017) provides a structure for evaluating and developing these competencies. This framework identifies six areas of digital competence for educators: professional engagement, digital resources, teaching and learning, assessment, empowering learners, and facilitating students' digital competence.

Zhai et al. (2021), in a study involving 396 university teachers in China, found that teachers' digital competencies were significantly related to their intention to use AI in teaching ($\beta = 0.31$, $p < 0.001$). Furthermore, Fernández-Batanero et al. (2020), in research conducted with 1,194 Spanish teachers, observed that digital competencies were positively correlated with the perceived usefulness of emerging technologies in education, including AI ($r = 0.41$, $p < 0.01$).

Rune Johan Krumsvik (2020) proposes a model of teachers' digital competence that, although not specifically focused on AI, offers a relevant framework for understanding the skills required in the digital era. This model includes four main components: basic digital skills, ICT-related didactic competence, learning strategies, and digital education.

Pérez-Escoda and Fernández-Villavicencio (2016) applied this model in a study involving 80 Spanish university professors, where they found that the level of digital competence significantly influenced the integration of advanced technologies into teaching ($r = 0.62$, $p < 0.001$). Although this study did not focus specifically on AI, it provides evidence regarding the importance of digital competencies in the adoption of new educational technologies.

One aspect to consider is that the relationship between teachers' digital competencies and AI adoption is not simply linear.

On the other hand, Tsai et al. (2022) found that AI adoption is mediated by factors such as AI self-efficacy and teachers' pedagogical beliefs. Their study suggests that interventions aimed at improving AI adoption should address not only technical skills but also teachers' beliefs and attitudes toward technology in education.

Likewise, continuous professional development plays an important role in the development of teachers' digital competencies. In this context, these competencies are fundamental for the effective adoption of new technologies, including those based on Artificial Intelligence (AI).

Kaliisa et al. (2022) examined various professional development approaches aimed at improving university teachers' technological skills. Their study, which involved 78 professors from three Norwegian universities over an 18-month period, revealed that training programs combining theory and practical classroom application are particularly effective.

Specifically, participants who received practical training demonstrated a significant increase in technological self-efficacy ($d = 0.82$, $p < 0.001$) and in the frequency of advanced technology use in their teaching ($d = 0.74$, $p < 0.001$), compared to those who received only theoretical training.

Although this study did not focus exclusively on AI, its findings are relevant for understanding how to better prepare teachers for the integration of emerging technologies in higher education.

It is important to note that teachers' digital competencies do not develop in a vacuum, but are instead influenced by the institutional and cultural context. Sánchez-Cruzado et al. (2021) examined how institutional factors, such as policies supporting technological innovation and

organizational culture, influence the development of teachers' digital competencies. Their findings underscore the importance of a holistic approach that considers both individual development and the organizational context in promoting digital competencies for AI adoption.

Attitudes Toward AI

A determining factor in attitudes toward AI is the perception of its role within the educational context. Nazaretsky et al. (2022) investigated how different ways of presenting AI influence teachers' trust in these systems. The results showed that teachers exposed to descriptions of AI as a support tool reported significantly higher levels of trust compared to those who were presented with AI as a potential substitute.

Furthermore, the group that perceived AI as a support tool demonstrated a greater willingness to integrate these technologies into their teaching practice. These findings highlight how the way AI capabilities are presented and communicated can significantly influence their acceptance in the educational field.

Ethical concerns are another crucial component of attitudes toward AI in education. Yadegaridehkordi et al. (2022) found that teachers' perceptions regarding data privacy, algorithmic fairness, and the transparency of AI systems considerably influence their attitudes toward the adoption of these technologies. Their study suggests that proactively addressing these ethical concerns may improve attitudes and, consequently, the adoption of AI in higher education.

Self-efficacy in the use of AI also emerges as a crucial factor in shaping attitudes. Ronny Scherer et al. (2019) demonstrated that teachers' self-efficacy in using AI is strongly correlated with positive attitudes toward these technologies and with a greater intention to adopt them in educational practice. Their findings suggest that interventions aimed at improving teachers' AI self-efficacy could be an effective strategy for promoting positive attitudes and increasing adoption.

Zhai et al. (2021) analyzed variations in attitudes toward AI among different groups of university teachers. Their systematic review, which covered 89 studies published between 2010 and 2020, revealed significant patterns in teachers' perceptions of AI. The qualitative analysis indicated that science and technology professors generally displayed a more favorable disposition toward AI compared to their colleagues in the humanities.

The authors attribute this difference to the nature of the disciplines and prior familiarity with advanced technologies. The study notes that humanities teachers more frequently expressed concerns about the potential impact of AI on critical thinking and creativity.

Additionally, the researchers observed that teaching experience influenced attitudes toward AI, although they did not provide specific quantitative data regarding this relationship. These findings suggest the need to consider disciplinary and experiential differences when developing strategies for AI adoption in higher education.

Institutional Support

Institutional support is a critical factor in the adoption of AI in higher education. The Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Viswanath Venkatesh et al. (2003), later updated by Yogesh K. Dwivedi et al. (2019) to include AI-specific considerations, highlights the importance of institutional facilitating conditions. This includes not only technological infrastructure, but also support policies, continuous training, and institutional leadership in educational innovation.

A recent study by Tsai et al. (2022) examined how different forms of institutional support influence university teachers' adoption of AI. Their findings suggest that technical support, continuous professional development, and policies encouraging innovation are the most influential factors. Furthermore, they found that institutional leadership actively modeling the use of AI has a significant effect on teachers' willingness to adopt these technologies.

Organizational culture also plays a crucial role in AI adoption. Huang et al. (2021) investigated how different types of organizational cultures (e.g., hierarchical, clan, market, and adhocratic) influence AI adoption in higher education institutions. Their results indicate that adhocratic cultures, characterized by flexibility and innovation, are more conducive to AI adoption.

These findings suggest that considering and potentially transforming organizational culture could be a crucial component of effective strategies for AI adoption in higher education.

Institutional support is also reflected in the allocation of resources and time for experimentation with AI. Herodotou et al. (2021) studied the implementation of AI-based learning analytics systems in an open university. They found that providing teachers with protected time to experiment with these technologies, together with technical and pedagogical support, was a determining factor for successful adoption.

This finding demonstrates how workload and time pressures faced by teachers can significantly influence the implementation of new technologies. Considering these factors may be fundamental in designing effective strategies for integrating AI into the educational environment.

Interdepartmental collaboration emerges as another important aspect of institutional support. Liu et al. (2021) investigated how collaboration between academic departments and educational technology units affects AI implementation in higher education. Their results suggest that institutions fostering close collaboration between these departments are more successful in implementing AI solutions.

The authors suggest that overcoming departmental barriers and promoting an integrated approach is essential for the effective adoption of AI in educational settings.

On the other hand, it is also crucial to examine how institutional support interacts with external policies and regulations. In this regard, Ben Williamson and Rebecca Eynon (2020) analyze how national and international AI policies in education influence institutional adoption strategies.

Their work underscores the importance of higher education institutions not only providing internal support, but also proactively navigating the evolving political and regulatory landscape related to AI in the educational field.

Technological Infrastructure

Although technological infrastructure is necessary, recent studies suggest that its impact on AI adoption may be less direct than previously believed. The sociotechnical model of AI adoption in education proposed by Neil Selwyn (2019) argues that infrastructure should be considered alongside social and organizational factors in order to fully understand its influence on AI adoption.

A recent study by Zawacki-Richter et al. (2019) examined the relationship between technological infrastructure and AI adoption in universities across 20 countries. Their findings suggest that, although robust infrastructure is necessary, it is not sufficient on its own to guarantee adoption. Factors such as staff training, institutional policies, and organizational culture were found to be equally important.

The quality and reliability of infrastructure also play a crucial role. Ramírez-Montoya et al. (2021) found that teachers' perceptions regarding the reliability of AI systems significantly influence their willingness to adopt them. This study underscores the importance not only of implementing AI infrastructure, but also of ensuring its consistent and reliable operation.

Infrastructure scalability emerges as another critical factor. Liu et al. (2021) examined the challenges of scaling AI implementations in higher education. Their findings suggest that institutions must carefully consider how their infrastructure can grow and adapt as AI adoption increases, thereby highlighting the importance of long-term planning in infrastructure investments.

Another aspect of vital importance is evaluating equity in access to AI infrastructure. Justin Reich (2021) indicates that disparities in technological infrastructure among institutions may exacerbate existing educational inequalities. His work emphasizes the need for policies that ensure an equitable distribution of AI resources in higher education.

Ethical and Pedagogical Challenges in AI Adoption

The previously discussed points suggest that the adoption of AI in higher education is not without ethical and pedagogical challenges. For this reason, Wayne Holmes et al. (2022) propose an ethical framework for AI in education that addresses issues of privacy, equity, and transparency. This framework provides a theoretical basis for evaluating and mitigating the risks associated with implementing AI in educational contexts.

One of the main ethical challenges is the privacy of student data. Prinsloo and Slade (2022) examined the ethical implications of collecting and using student data in educational AI systems. Their findings highlight the need for clear informed consent and data protection policies, as well as the importance of transparency regarding how student data is used.

Equity and bias in AI systems are another crucial concern. Baker and Hawn (2022) analyzed how biases in training data can lead to inequitable outcomes in educational AI systems. Their work highlights the importance of auditing AI systems to detect and mitigate bias, as well as the need for diversity within the teams developing these technologies.

From a pedagogical perspective, the concept of "pedagogically informed AI" proposed by Rose Luckin and Mutlu Cukurova (2019) offers a theoretical approach for integrating AI in ways that support and enhance existing pedagogical practices rather than replacing them. This approach emphasizes the importance of keeping both the teacher and the student at the center of the educational process, using AI as a supportive tool.

It is also valuable to consider the long-term implications of AI in higher education. Neil Selwyn (2023) argues that the widespread adoption of AI could lead to a fundamental redefinition of the role of the teacher and the very nature of higher education itself. His work highlights the need for ongoing and critical dialogue about the future of education in the AI era.

Final Reflections on the Literature Review

The studies analyzed highlight the fundamental role of teachers' digital competencies, their attitudes toward AI, institutional support, and technological infrastructure. The interconnection among these factors becomes evident, given that digital competencies not only directly affect AI adoption, but also influence teachers' attitudes. Institutional support encompasses aspects such as continuous professional development, incentive policies, and organizational culture, extending beyond the mere provision of infrastructure.

Ethical and pedagogical challenges emerge as crucial considerations in this adoption process. The balance between technological innovation and the protection of student privacy, equity in access to and use of AI, alongside the preservation of the humanistic values of education, are recurring themes in recent literature.

Taken together, this review suggests that the effective adoption of AI in higher education requires a holistic approach that considers technological, human, organizational, and ethical aspects, while recognizing that this process entails an educational transformation that demands continuous critical reflection on the goals and values of higher education in the digital era.

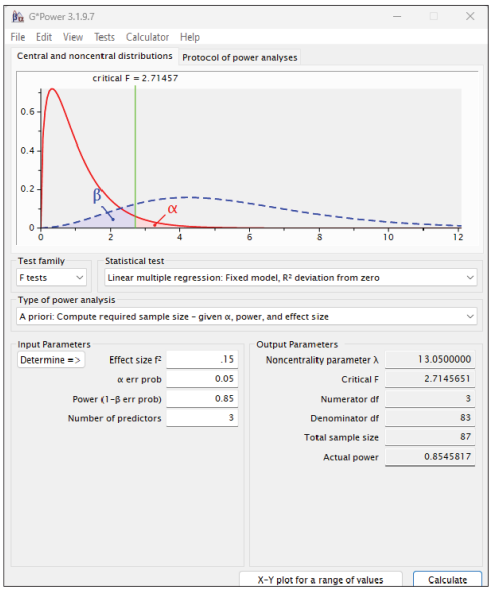
Methodology

As previously mentioned, the main objective of this research is to analyze the factors that influence the effective adoption of Artificial Intelligence in higher education in the Dominican Republic, with special attention to the interaction between teachers' digital competencies, attitudes toward AI, institutional support, and the available technological infrastructure.

A quantitative, cross-sectional, and explanatory study was conducted using structural equation modeling to examine the complex relationships among the variables. The sample consisted of 101 university professors from the Dominican Republic, selected through simple random sampling. This sample size exceeded the minimum required 87 participants,

calculated a priori through a power analysis using G*Power (see Figure 1) and considering a medium effect size ($f^2 = 0.15$), a statistical power of 0.85, a significance level of 0.05, and three predictors for a multiple regression analysis.

Figure 1. *Result of the sample size calculation for the study.*



Fuente: Análisis con G*Power 3.1.9.7

Analysis of Results

Partial least squares structural equation modeling (PLS-SEM) was employed using SmartPLS 4 Version 4 (Ringle et al., 2023), an appropriate method for predictive studies in the social sciences. The corresponding analysis was conducted in two stages, encompassing the evaluation of both the measurement model and the structural model.

The evaluation of the measurement model included the analysis of construct reliability (through Cronbach's Alpha and composite reliability), convergent validity (through Average Variance Extracted), and discriminant validity using the Heterotrait-Monotrait ratio, as well as collinearity through Variance Inflation Factors (VIF).

The evaluation of the structural model was conducted through partial least squares structural equation modeling (PLS-SEM), using the bootstrapping technique with 5,000 subsamples to assess the statistical significance of the path coefficients. Likewise, path coefficients (β) and coefficients of determination (R^2) were examined to measure the explained variance in the endogenous variables.

This comprehensive methodological approach provided a rigorous and reliable evaluation of the predictive and explanatory capacity of the proposed structural model, allowing for a robust interpretation of the relationships among the factors influencing AI adoption in Dominican higher education.

Evaluation of the Measurement Model

Construct Reliability

As shown in Table 1, construct reliability was assessed using Cronbach's Alpha and composite reliability (ρc). The values exceeded the 0.70 threshold for all constructs (Attitude toward AI: α = 0.860, ρc = 0.860; Effective AI Adoption: α = 0.828, ρc = 0.826; Teachers' Digital Competencies: α = 0.811, ρc = 0.811), indicating adequate reliability (Hair et al., 2022).

Regarding convergent validity, also presented in Table 1, it was examined through Average Variance Extracted (AVE). All constructs showed AVE values above the 0.50 threshold (Attitude toward AI: 0.672; Effective AI Adoption: 0.614; Teachers' Digital Competencies: 0.683), thereby confirming convergent validity (Fornell & Larcker, 1981).

Table 1. *Construct reliability and validity.*

	Alfa de Cronbach	Fiabilidad compuesta (rho_a)	Fiabilidad compuesta (rho_c)	Varianza extraída media (AVE)
Actitud hacia IA	0.860	0.863	0.860	0.672
Adopción efectiva de IA en educación	0.828	0.828	0.826	0.614
Competencias digitales docentes	0.811	0.812	0.811	0.683

Fuente: Análisis del autor con Smart-PLS

As shown in Table 2, discriminant validity was assessed using the Heterotrait-Monotrait ratio (HTMT). All HTMT values were below the conservative threshold of 0.85, with the highest value (0.820) observed between Attitude toward AI and Effective AI Adoption, thereby demonstrating adequate discriminant validity (Henseler et al., 2015).

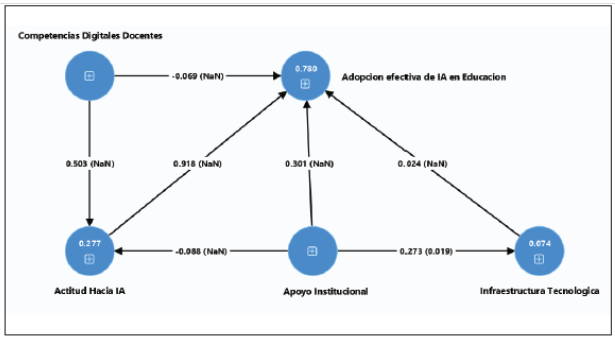
Table 2. *Heterotrait-Monotrait (HTMT) ratio matrix.*

	Actitud hacia IA	Adopción efectiva de IA en Educación	Apoyo institucional	Competencias digitales docentes
Adopción efectiva de IA en educación	0.820			
Apoyo institucional	0.182	0.158		
Competencias digitales docentes	0.517	0.347	0.179	
Infraestructura tecnológica	0.138	0.082	0.273	0.259

Fuente: Análisis del autor con Smart-PLS

Evaluation of the Structural Model

Figure 2. *Structural model.*



Fuente: Análisis del autor con Smart-PLS

The evaluation of the structural model was conducted through partial least squares structural equation modeling (PLS-SEM) using SmartPLS 4 (Ringle et al., 2023). The bootstrapping technique with 5,000 subsamples was employed to assess the statistical significance of the path coefficients, generating confidence intervals and t-values (Hair et al., 2022).

This procedure revealed, for example, that the relationship between Attitude toward AI and Effective AI Adoption was highly significant ($\beta = 0.918$, $p < 0.001$). Path coefficients (β) were examined to determine the strength and direction of the relationships among latent variables. Coefficients of determination (R^2) were calculated to measure the explained variance in the endogenous variables (Chin, 1998), highlighting that the model explains 78% of the variance in Effective AI Adoption ($R^2 = 0.780$).

This comprehensive methodological approach provided a rigorous and reliable evaluation of the predictive and explanatory capacity of the proposed structural model, allowing for

a robust interpretation of the relationships among the factors influencing AI adoption in Dominican higher education.

Techniques and Instruments

Data were collected through an electronic survey. The key latent variables considered were: Teachers' Digital Competencies, Attitude toward AI, and Effective Adoption of AI in Education. Additionally, the manifest variables Technological Infrastructure and Institutional Support were considered.

The survey instrument was validated through a process that included:

1. **Content validity:** A panel of three experts in educational technology and research methodology evaluated the relevance and clarity of each item. The Content Validity Index (CVI) was calculated, and only items with a CVI > 0.80 were retained.
2. **Reliability:** Cronbach's Alpha was calculated for each subscale, yielding values between 0.82 and 0.91, indicating high internal consistency.
3. **Pilot study:** A pilot test was conducted with 21 university teachers to evaluate item comprehension and response time. Based on the feedback received, minor adjustments were made to the wording of some items.

The electronic survey was distributed to randomly selected participants. Data were collected regarding the demographic and professional characteristics of the participants, as well as their responses to the measurement scales of the study variables.

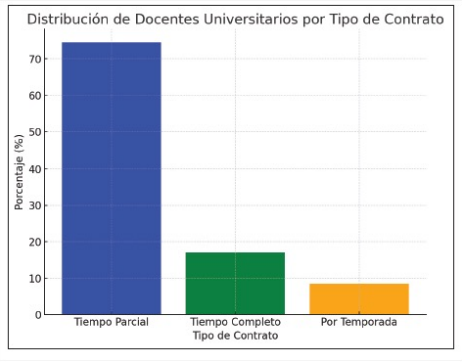
Finally, it is important to note that standard ethical protocols for social science research were followed, including informed consent from participants and the confidentiality of the collected data.

Results

Participant Characteristics

The study included a diverse sample of university teachers, predominantly part-time faculty members (74.5%), with a minority of full-time faculty (17%) and seasonal faculty (8.5%). The following graph presents these results.

Figure 3. *Distribution of university teachers by type of contract.*



Regarding experience with digital technologies for teaching, nearly half of the participants (44.3%) reported having more than 10 years of experience, followed by 23.6% with 4 to 6 years of experience. The most represented disciplinary areas were Social Sciences and Humanities (41.3%) and Engineering and Technology (29.8%), with additional representation from Natural and Exact Sciences (14.9%), as well as other disciplines to a lesser extent.

The following two graphs illustrate this distribution.

Figure 4. *Experience in the use of digital technology.*

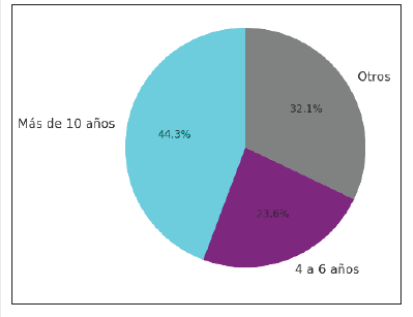
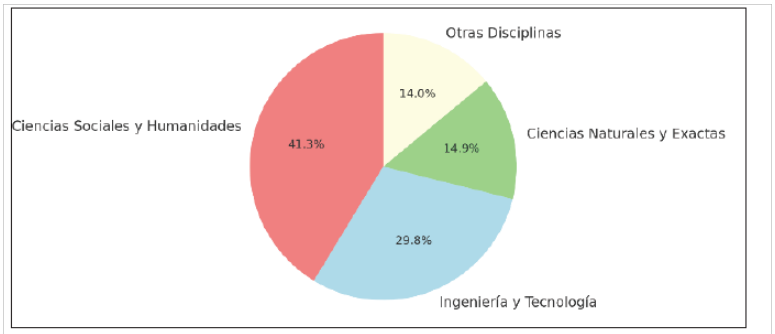
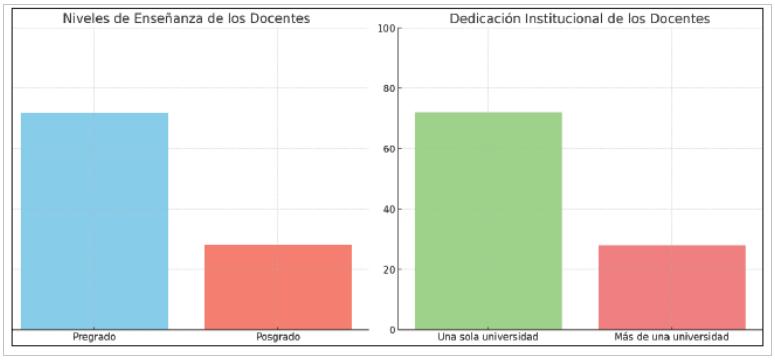


Figure 5. *Participants' disciplinary areas.*



As shown in the following graph, the majority of participants (71.8%) teach at the undergraduate level, while 28.2% also teach at the graduate level. It is noteworthy that 72% of the teachers work exclusively at a single university. In terms of institutional diversity, 28% of the professors teach at more than one university.

Figure 6. *General overview of the study population.*



This characterization provides a general overview of the university teachers included in the study, reflecting the diversity in professional dedication, technological experience, disciplinary fields, and teaching levels within contemporary Dominican higher education.

Evaluation of the Measurement Model

As shown in Table 1, the analysis of the measurement model revealed robust results for all constructs. Reliability, assessed through Cronbach's Alpha and composite reliability (ρc), exceeded the 0.70 threshold recommended by Hair et al. (2022) for all constructs: Attitude toward AI (α = 0.860, ρc = 0.860), Effective AI Adoption in Education (α = 0.828, ρc = 0.826), and Teachers' Digital Competencies (α = 0.811, ρc = 0.811).

These results not only indicate strong internal consistency, but also reflect the careful selection and adaptation of the scales to the Dominican context, a crucial aspect in cross-cultural research on technology adoption (Straub et al., 2002).

Convergent validity, assessed through Average Variance Extracted (AVE), produced results exceeding the 0.50 threshold established by Fornell and Larcker (1981): Attitude toward AI (0.672), Effective AI Adoption in Education (0.614), and Teachers' Digital Competencies (0.683). These values not only satisfy statistical criteria, but also suggest a strong conceptual alignment between the items and their respective constructs, thereby reinforcing the content validity of the instrument (MacKenzie et al., 2011).

Discriminant validity, confirmed through the analysis of the Heterotrait-Monotrait ratio (HTMT) presented in Table 2, showed values below the conservative threshold of 0.85 proposed by Henseler et al. (2015). The highest value (0.820) between Attitude toward AI and Effective AI Adoption in Education suggests a close yet distinguishable relationship between these constructs, which is consistent with the literature on technology adoption in education (Scherer et al., 2019).

Evaluation of Collinearity

As shown in Table 4, the Variance Inflation Factor (VIF) values for all indicators were below the conservative threshold of 3 (Hair et al., 2022), ranging between 1.000 and 1.443. This absence of problematic collinearity not only validates the specification of the model, but also reinforces the reliability of the estimated path coefficients, a decisive aspect for the accurate interpretation of results in PLS-SEM models (Ringle et al., 2023).

Table 3. *Collinearity statistics (VIF) – Internal Model.*

	Actitud hacia IA	Adopción efectiva de IA en educación	Infraestructura tecnológica
Actitud hacia IA	1.033	1.384	1.00
Apoyo institucional	1.033	1.107	
Competencias digitales docentes	1.033	1.443	
Infraestructura tecnológica		1.137	

Fuente: Análisis del autor con Smart-PLS

Evaluation of the Structural Model

The analysis of the structural model, based on effect sizes (f^2) as shown in Table 3, revealed significant findings:

Table 4. *Effect sizes (f^2) of one variable on another.*

	Actitud hacia IA	Adopción efectiva de IA en educación	Infraestructura tecnológica
Actitud hacia IA		2.761	
Apoyo institucional	0.01	0.372	0.08
Competencias digitales docentes	0.339	0.015	
Infraestructura tecnológica		0.002	

Fuente: Análisis del autor con Smart-PLS

Attitude toward AI → Effective AI Adoption in Education (f^2 = 2.761): This large effect underscores the centrality of teachers' attitudes in technology adoption, aligning with Theory of Planned Behavior proposed by Icek Ajzen (1991) and with recent studies on AI adoption in education (Sharma & Mantri, 2024).

Institutional Support → Effective AI Adoption in Education (f^2 = 0.372): The fact that this effect stands out as large highlights the importance of the organizational context, in accordance with the Unified Theory of Acceptance and Use of Technology developed by Viswanath Venkatesh et al. (2003), which emphasizes the role of facilitating conditions in technology adoption.

Teachers' Digital Competencies → Attitude toward AI (f^2 = 0.339): This medium-to-large effect suggests that teachers' technological skills significantly influence their attitudes toward AI, aligning with the Technological Pedagogical Content Knowledge framework proposed by Punya Mishra and Matthew J. Koehler (2006).

Teachers' Digital Competencies → Effective AI Adoption in Education (f^2 = 0.015) and Technological Infrastructure → Effective AI Adoption in Education (f^2 = 0.002): These small to very small effects suggest that, although these factors are necessary, they are not sufficient on their own to drive AI adoption, a finding that challenges some common assumptions regarding technology adoption in education (Selwyn, 2016).

Discussion and Conclusions

This research aimed to analyze the factors influencing the effective adoption of Artificial Intelligence (AI) in Dominican higher education. The results obtained, in light of recent literature, reveal the complexity of this process and offer significant implications for both theory and educational practice.

The most significant finding of the study is the predominance of teachers' attitudes as the most critical factor in AI adoption. This result aligns with the AI Acceptance Model in Education (AI-MEA) proposed by Timothy Teo et al. (2021), which emphasizes the importance of perceptions of pedagogical usefulness and ethical concerns in shaping attitudes toward AI.

The results presented here extend this model to the Dominican context, suggesting its cross-cultural applicability. However, they contrast to some extent with the study by Nazaretsky et al. (2022), which found that framing AI as a support tool, rather than as a replacement for teachers, was crucial for fostering positive attitudes. In the Dominican context, attitudes appeared to be more influenced by perceptions of usefulness than by framing, suggesting the need for communication strategies adapted to the local context.

Institutional support emerged as the second most influential factor, which is consistent with the updated UTAUT model proposed by Yogesh K. Dwivedi et al. (2019). However, the present results suggest a more complex relationship between institutional support and AI adoption than that proposed by the UTAUT model.

Consistent with the findings of Tsai et al. (2022), technical support, continuous professional development, and policies encouraging innovation were found to be crucial. Nevertheless, this study also revealed the importance of interdepartmental collaboration, an aspect not addressed in previous studies but which proved critical in the national context. This finding aligns with the work of Liu et al. (2021) regarding the importance of collaboration between academic departments and educational technology units.

The results concerning the indirect effect of digital competencies on AI adoption, mediated by attitudes, are supported by the work of Tsai et al. (2022). This finding underscores the importance of considering not only technical skills, but also how these skills influence teachers' beliefs and attitudes toward technology.

However, the present study goes further by contextualizing these competencies within the DigCompEdu framework proposed by Christine Redecker (2017) and the teacher digital competence model proposed by Rune Johan Krumsvik (2020). This contextualization allows for a more nuanced understanding of which specific aspects of digital competencies are most relevant for AI adoption in higher education.

Surprisingly, technological infrastructure showed the lowest effect on AI adoption. This finding aligns with the sociotechnical model of AI adoption in education proposed by Neil Selwyn (2019), who argues that infrastructure must be considered together with social and organizational factors.

The results presented here also support the findings of Zawacki-Richter et al. (2019), who found that although robust infrastructure is necessary, it is not sufficient on its own to guarantee adoption. This suggests that AI implementation strategies in higher education must go beyond the basic provision of technology and address broader aspects of the educational ecosystem.

Although the present study did not focus specifically on ethical and pedagogical challenges, these emerged as underlying issues of importance in AI adoption. The findings align closely with the ethical framework for AI in education proposed by Wayne Holmes et al. (2022), which addresses issues of privacy, equity, and transparency.

Concerns regarding these ethical aspects, especially in relation to student data privacy, resemble the findings of Prinsloo and Slade (2022). This suggests the need to integrate ethical considerations into AI adoption strategies from the earliest stages.

These findings have significant implications for both practice and theory, as outlined below:

1. AI implementation strategies should prioritize the development of positive attitudes among teachers, not solely technical training. This could be achieved through professional development programs addressing not only technical skills but also the pedagogical and ethical implications of AI, as suggested by the "pedagogically informed AI" approach proposed by Rose Luckin and Mutlu Cukurova (2019).

2. It is crucial to develop coherent institutional policies that foster an ecosystem of innovation around AI. This involves not only providing technological resources, but also creating support structures, incentives, and opportunities for interdepartmental collaboration, as suggested by Liu et al. (2021).

3. Digital competency development programs should integrate critical reflection on the pedagogical implications of AI, not merely technical skills. This aligns with the teacher digital competence model proposed by Rune Johan Krumsvik (2020), which extends beyond technical skills to include the ability to critically evaluate and apply AI within educational contexts.

4. More sophisticated theoretical frameworks are needed to capture the complexity of the interactions among technology, pedagogy, and institutional context in AI adoption. The findings discussed here suggest the need to integrate models such as the AI-MEA proposed by Teo et al. (2021) with sociotechnical perspectives such as that of Neil Selwyn (2019), in order to achieve a more holistic understanding of AI adoption in higher education.

On another note, it is also important to recognize the limitations of this study. The cross-sectional nature of the research restricts causal inferences. Future studies could benefit from longitudinal designs, such as the longitudinal SEM approach proposed by Morin et al. (2023), to examine how AI adoption evolves over time. Furthermore, the focus on Dominican higher education may limit the generalizability of the findings to other contexts.

Therefore, cross-cultural comparative studies are considered necessary to examine how contextual factors shape AI adoption, following the approach proposed by Zawacki-Richter et al. (2019).

In conclusion, this study makes a significant contribution to understanding AI adoption in higher education by revealing the complexity of this process and the need for holistic

approaches that consider human, organizational, and technological factors. Only through a comprehensive understanding will it be possible to fully harness the transformative potential of AI in higher education while navigating the ethical, pedagogical, and social challenges posed by this emerging technology.

Future research should further explore the interaction among these factors and examine how they evolve as AI becomes more deeply integrated into educational systems.

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