DETERMINANTS OF ARTIFICIAL INTELLIGENCE ADOPTION IN HIGHER EDUCATION: AN IMPORTANCE–PERFORMANCE MAP ANALYSIS APPROACH

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Abstract

Rapid advancements in artificial intelligence (AI), particularly Generative AI, are fundamentally transforming higher education. The aim of this study is to identify the determinants of AI acceptance among Generation Z students and to extend existing technology adoption models by integrating the methods of Partial Least Squares Structural Equation Modeling and Importance–Performance Map Analysis. Empirical data were collected through a questionnaire survey conducted among university students. The model included Perceived Informedness, Perceived Knowledge, Perceived Usefulness, and Perceived Risk. The Partial Least Squares Structural Equation Modeling results confirmed the significance of Perceived Knowledge and Perceived Usefulness, while Perceived Risk was not found to be significant. The Importance–Performance Map Analysis revealed that Perceived Knowledge represents the most important and best-developed factor, whereas Perceived Usefulness constitutes the key area for improvement. Perceived Informedness shows a limited impact despite its relatively high level of performance. The findings highlight the need to focus on the practical applicability of AI as the primary driver of its adoption in the higher education environment.

Key words:
Generative Artificial Intelligence, Higher Education, Adoption models, PLS-SEM, IPMA

JEL Classification O33, C83, I23
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INTRODUCTION

In recent years, education has been undergoing a transformation driven by digitalization and modern technologies. Technology increasingly permeates processes such as information handling, the organization of learning, and the preparation of students for life in a digitally integrated world. Generative AI (GAI) is rapidly entering this domain, becoming easily accessible and widely used by both students and educators, often beyond formally established rules. Its development not only affects how learning and teaching are conducted but also reshapes the roles of students and teachers while increasing demands on educational management. Artificial Intelligence (AI) refers to systems capable of performing tasks that traditionally require human intelligence, such as learning, decision-making, and information processing (Holmes, 2023). Its rapid development contributes to broader societal changes reflected in education, raising concerns about responsible use, reliability, and transparency. For educational management, it is therefore essential not only to monitor technological capabilities but also to understand their implications for learning processes and institutional outcomes (Miao & Holmes, 2021; Slavov et al., 2023). A clearly defined understanding of AI is crucial, as it influences technology selection, governance, and the development of student competencies.

The rapid diffusion of GAI into education has created a paradox in both policy and practice: while institutions embrace its potential for personalization, automation, and improved access, they simultaneously face risks related to privacy, academic integrity, and inequality. Its implementation requires clear guidelines, adapted assessment mechanisms, and continuous professional development of educators. Governance should also define responsibility for tool selection, use, and oversight (Grandström & Oppi, 2025; Miao & Holmes, 2021). UNESCO (2023) issued the first global guidance on generative AI in education, emphasizing ethical use, data protection, and human-centered approaches, while OECD highlights that most countries rely on non-binding guidelines, shifting responsibility to institutions. Existing research points to both opportunities (e.g., personalization and enhanced feedback) and risks (e.g., integrity and digital inequality), underscoring the need for theoretically grounded empirical models explaining AI adoption and continued use.

The aim of this study is to examine the determinants of AI adoption in higher education by combining Partial Least Squares Structural Equation Modeling with Importance–Performance Map Analysis, enabling not only the identification of significant relationships but also the assessment of their practical relevance. This study contributes to the literature by demonstrating that the gap between perceived knowledge and perceived usefulness represents a critical barrier in AI adoption, which is not captured by traditional TAM-based models.

LITERATURE OVERVIEW

Generative AI tools accelerate information retrieval, summarization, and data processing. In doing so, they contribute to higher productivity and more efficient utilization of human resources (U.S. Government Accountability Office, 2023; Uddin et al., 2025). These tools is becoming a factor that shapes the direction of organizations and their approaches to change management. In the field of education, GAI is being adopted at an exceptionally rapid pace. Generative tools are now widely accessible, and students increasingly rely on them in their studies, often even without the formal integration of AI into the curriculum. GAI influences learning processes, students' approaches to working with information, and their strategies for solving academic tasks (Miao & Holmes, 2021). Students use GAI tools for language editing, translation, writing support, explaining subject matter, and checking assignments (Granström & Oppi, 2025). From a teaching perspective, these tools can support the creation and adaptation of learning materials and help tailor content to the individual needs of students (Uddin et al., 2025). However, the rapid diffusion of GAI in educational settings also creates new challenges for institutions. There is an increasing need to establish clear rules for the use of AI and to make informed decisions regarding the integration of generative tools into education. Therefore, the practical use of GAI must be closely linked with issues of control, accountability, and technological limitations (Uddin et al., 2025; Sengar et al., 2024).

The field of education is undergoing a transformation under the influence of digitalization and modern technologies. The use of technology increasingly permeates processes such as information handling, the organization of learning, and the preparation of students for life in a world where digital technologies are an integral part of everyday reality (Slavov et al., 2023). GAI is entering this development at a rapid pace, as it is easily accessible and both students and educators have already begun to use it in practice, often beyond formally established rules. Its development is reshaping the roles of both students and teachers within the educational process and increasing the demands placed on the management of educational processes. Educational management encompasses the planning, organization, implementation, and evaluation of educational activities at the level of institutions, educational systems, or specific programs. In recent years, it has been increasingly influenced by digital transformation, of which AI has become an integral component. Its implementation does not represent merely a technological innovation, but also a transformation of educational processes themselves. For this reason, GAI is already becoming a subject of strategic management within educational institutions (Miao & Holmes, 2021). The rapid proliferation of generative tools is placing increasing pressure on educational institutions to respond systematically. GAI can therefore no longer remain solely an individual initiative of teachers or students, but requires a coordinated and managed approach from institutional leadership. It is necessary to determine how Artificial Intelligence should be integrated into the educational process. A distinction must be made between the use of AI in teaching and administration, and education about AI as part of the curriculum. In the first case, AI serves to support teaching, the preparation of materials, and the streamlining of administrative processes. In the second case, the focus is on developing an understanding of how AI works, its limitations, and its impact on society (Holmes, 2023). The implementation of GAI requires the establishment of clear usage guidelines, the adaptation of assessment mechanisms, and the professional development of educators. An essential component of governance is also the definition of responsibility for the selection of tools, the manner of their use, and the oversight of their application. Clearly defined processes help prevent ambiguity and can strengthen trust in institutional decision-making (Granström & Oppi, 2025; Miao & Holmes, 2021). The development of AI technologies also highlights the need to systematically build competencies among both students and educators. Educational management thus faces the challenge of maintaining a balance between the innovative potential of these tools and the need for clear rules, oversight, and data protection. Once these frameworks are established, it becomes possible to evaluate the actual benefits for teaching and learning.

The implementation of GAI has the potential to influence both learning processes and the functioning of educational institutions. Strategic documents of the European Union and UNESCO primarily emphasize benefits for students, who are at the center of the educational process. However, the impact of GAI also extends to teachers and institutional management; therefore, its implementation should take into account the broader organizational context (Slavov et al., 2023). One of the most frequently cited benefits is the personalization of learning, particularly through Self-Directed Learning (SDL) tools, which enable the adaptation of content, difficulty, and pace of instruction to individual student needs. This is expected to enhance flexibility and the ability to respond to diverse learning styles (Miao & Holmes, 2021). Another important area is the support of academic writing and access to information. The use of GAI in education brings a range of risks and challenges that must be taken into account. These relate to technological limitations as well as ethical, pedagogical, and organizational aspects. The implementation of generative tools should therefore not be automatically perceived as beneficial, but rather as a process requiring carefully designed policies and continuous evaluation of impacts (Granström & Oppi, 2025; Holmes, 2023). One of the most widely discussed issues is academic integrity. GAI enables the generation of texts, program code, and solutions to assignments, which may have significant negative implications for student autonomy. Unintentional plagiarism, as well as the deliberate misuse of such tools, represents a risk that necessitates the establishment of appropriate assessment mechanisms and clear usage guidelines. Research points to concerns about the weakening of critical thinking and creativity when AI tools are overused. In student learning, it is essential that learners engage in phases of planning, ongoing monitoring, and self-reflection. GAI can support these phases, for example, by explaining subject matter or helping to organize the learning process, but it can also bypass them by providing immediate solutions without requiring deeper cognitive processing. There are also concerns regarding the uncritical adoption of generated content without verification, the spread of inaccuracies caused by model hallucinations, and weaker evaluation of sources underlying generated information (Granström & Oppi, 2025).

Some studies also point to social and psychological factors. Excessive use of AI tools may limit direct interactions between students and teachers, as well as among students themselves. When communication is replaced by technology, feelings of isolation or weaker integration into the educational environment may emerge (Granström & Oppi, 2025). At the same time, the pace of development of Artificial Intelligence tools exceeds the capacity of educational systems to provide sufficient support to educators. Teachers may experience uncertainty, particularly when responding to the widespread use of AI by students. Another open question concerns the extent of the empirical foundation for implementing AI in education. Although research on its use is increasing, large-scale and independent studies on its long-term impact on educational outcomes remain limited. This reinforces the need for caution when shaping expectations and designing implementation strategies (Holmes, 2023). The challenges associated with GAI in education highlight the need for a long-term vision grounded in evidence, continuous evaluation of impacts, and clearly defined accountability (Miao & Holmes, 2021). The risks are closely linked to ethical and regulatory issues surrounding its use. Questions of regulation concern not only legislation, but also ethical principles, internal institutional policies, and the ways in which institutions protect students when working with GAI (Bellas et al., 2023). A portion of the recommendations and frameworks originates from the international and European context and is subsequently translated into national policies and specific school-level regulations. For this reason, UNESCO emphasizes the need for coherent direction, rules, and procedures that support educational objectives and the ethical use of GAI (Bellas et al., 2023). A significant development in this area is the Artificial Intelligence Act, which establishes a legal framework for the development, deployment, and use of AI systems within the European Union. The AI Act is based on a risk-based approach. This means that the higher the level of risk a particular system poses, the stricter the rules that apply to it (Kop, 2021). The AI Act also demonstrates that, although something may be technologically feasible, it is not necessarily acceptable within the educational context (Regulation (EU) 2024/1689, 2024).

International organizations and academic literature emphasize transparency, accountability, fairness, and privacy protection in the use of AI systems in education (Granström & Oppi, 2025; Sengar et al., 2024). A key ethical issue also concerns how GAI handles student data and where the boundaries of acceptable use lie. In the educational context, this is not only about technical data protection, but also about trust, awareness, and careful handling of data related to students' performance, behavior, and activities. The issue is not merely whether data are formally protected, but also whether they are used sensitively and with respect for students (Sengar et al., 2024). Closely related to regulation and ethics is the development of AI literacy. Beyond establishing rules and highlighting risks, it is essential that students and educators understand what Artificial Intelligence can do, where its limitations lie, and how to critically assess when its outputs should be verified or questioned. The development of AI literacy can help prevent the use of AI without sufficient understanding of its capabilities, limitations, and associated risks (Miao & Holmes, 2021; Hornberg et al., 2023).

AI Literacy represents a broader set of knowledge, skills, and attitudes that enable individuals to understand how GAI works and to use it appropriately. It includes an understanding of the fundamental principles of AI, the ability to critically evaluate its outputs, and the capacity to apply this knowledge across different contexts (Kong et al., 2021; Dai et al., 2020). As part of students' digital competencies, AI literacy is recommended to be integrated into curricula. However, this does not imply merely introducing it as a standalone topic or providing one-time exposure to tools. Rather, it is a competence that should be developed continuously and interconnected with other subjects and areas of education. For this reason, UNESCO recommends that AI should appear not only in computer science education but also in subjects where there is scope to address its societal impact, ethical considerations, and practical implications for everyday life. Reviews of research on AI in higher education highlight both opportunities (enhanced feedback and personalization) and persistent concerns (academic integrity and digital inequality). They therefore emphasize the need for theoretically grounded empirical models that explain whether and why students adopt AI and why they continue to use it (Kasneci et al., 2023). More recent studies reinforce these issues: Dwivedi et al. (2023) point to the transformative yet disruptive potential of ChatGPT; Rudolph et al. (2023) highlight implications for traditional assessment; Mhlanga (2023) stresses the need for responsible implementation; Holmes et al. (2022) call for ethical frameworks; and Tlili et al. (2023) examine the paradoxical role of chatbots in education.

Existing adoption research primarily relies on the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB), which capture perceived usefulness, ease of use, social norms, and control, but tend to overlook motivational needs that support long-term use. One of the more recent studies by Tbaishat et al. (2026) examines the acceptance of GAI in higher education using an integrated TAM–TPB–SDT framework, where Self-Determination Theory (SDT) is incorporated. The findings indicate that adoption is shaped not only by cognitive evaluations, such as perceived usefulness and ease of use, but also by motivational needs, namely autonomy, competence, and social influences. The development and examination of integrated models of GAI acceptance in higher education, involving all relevant stakeholders, is currently of critical importance. The results of these studies provide concrete recommendations for universities: to design AI-supported collaborative learning activities that foster relatedness, to invest in the development of digital competencies that enable confident use, and to provide students with autonomy in integrating AI into their academic work. At the same time, these findings confirm the value of integrating cognitive, social, and motivational perspectives in explaining AI adoption.

METHODOLOGY

Research Design, Conceptual Model, and Sample

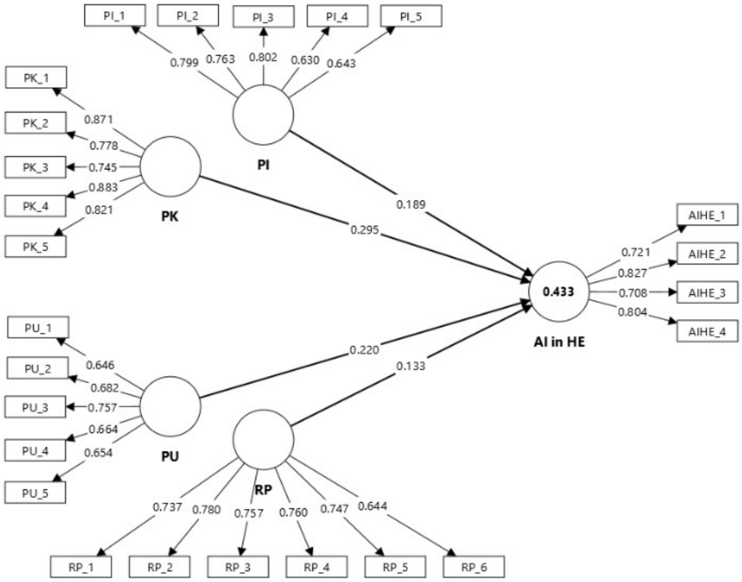
The present study builds on prior research in which a model of the determinants of Artificial Intelligence adoption in higher education was tested using Partial Least Squares Structural Equation Modeling.The conceptual model consists of five latent constructs and their causal relationships. The dependent variable of the model is the construct Artificial Intelligence in Higher Education (AI in HE), which represents the level of acceptance and perception of the use of AI technologies in education. This construct is influenced by four exogenous variables: Perceived Informedness (PI), Perceived Knowledge (PK), Perceived Usefulness (PU), and Perceived Risk (RP). The model was tested as a reflective structural model with direct relationships between the individual constructs. Building on these results, the objective of the present study is to extend the interpretation of the model using IPMA, which enables the identification of key factors in terms of their importance and performance. The IPMA map provides a more detailed interpretation of the structural model by simultaneously considering both the importance and the performance of individual constructs.

The research sample consisted of respondents belonging to Generation Z, representing a digitally native population with a high level of exposure to modern technologies. Data collection was conducted online using the Computer-Assisted Web Interviewing (CAWI) method. The sample size comprised 130 respondents, with a response rate of 71%.

Operationalization of Constructs

The questionnaire was developed based on established theoretical models of technology adoption, particularly the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), which were adapted to the context of AI technologies. The measurement instrument followed a multi-item approach, with individual constructs operationalized through items adopted and adapted from relevant literature. The questionnaire consisted of 25 items, with each construct measured by multiple indicators. Respondents evaluated each statement using a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). The model of identified and statistically significant causal relationships is presented in the following figure.

Figure 1: Semantic model



Source: Author's own elaboration

The resulting model was first assessed in terms of the measurement model using Convergent validity (Loadings, AVE), Internal Consistency reliability (Cronbach´s α, reliability ρ_A, reliability ρ_C) and Discriminant validity (FL criterion, HTMT, VIF). Subsequently, the structural model was evaluated using the coefficient of determination (R^2), effect size (f^2), Path Coefficient (β), and T-statistic values, as well as the predictive relevance of the model (Q^2). The predictive power of the estimated model was assessed using the Q^2 statistic, which is appropriate for reflective measurement models. The value obtained for Q^2 (AI in HE) was 0.381, which, according to Hair et al. (2024), indicates excellent predictive power of the model. The difference between RMSE values for PLS-SEM and linear modeling (LM) was negative, indicating that PLS-SEM produces a lower prediction error compared to LM.

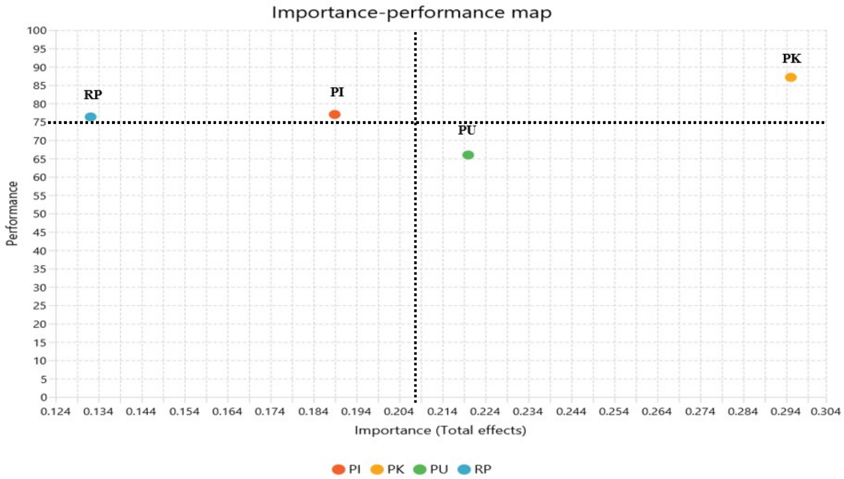
Based on the validated model, the Importance–Performance Map Analysis (IPMA) method was applied in order to extend the interpretation of the results. The IPMA (also called Importance-performance matrix, impact-performance map, or priority map analysis) extends the standard results reporting of path coefficient estimates and other parameters by adding a procedure that considers the average values of the construct scores (Hair et al., 2024). The IPMA contrasts the total effects, representing the predecessor construct´s importance in predicting a specific target construct, with their average construct scores indicating their performance. The rationale is to identify predecessor constructs that have a relatively high importance for explaining the target construct (those that have a strong total effect), but also have a relatively low performance (low average construct scores), so that improvements can be implemented. The IPMA draws on the five step procedure: Requirement check, Computation of the performance values, Computation of the importance values, Importance-performance map creation, Extension of the IPMA on the indicator´s level (Ringle, Sarsted, 2021).

For the analyzed model, Importance–Performance Map Analysis (IPMA) was conducted for the dependent construct AI in HE. Importance was determined based on the total effects of the exogenous variables: Perceived Informedness (PI), Perceived Knowledge (PK), Perceived Usefulness (PU), and Perceived Risk (RP) on AI in HE. Performance was calculated as the mean values of the latent variables, transformed to a 0–100 scale. This approach enables the identification of factors with a high impact on AI acceptance (e.g., PK, PU), areas with improvement potential (high importance but lower performance), and less relevant factors (e.g., RP in this model). The IPMA results thus represent a practical tool for formulating managerial recommendations in the implementation of AI in education.

FINDINGS

The figure presents IPMA results for the target construct AI in HE obtained using SmartPLS.

Figure 2: IPMA (construct level) for target construct independent constructs and its indicators



Source: Author's own elaboration

The horizontal axis represents the performance of the latent constructs, rescaled to a range from 0 to 100, while the vertical axis captures their importance, expressed as total effects derived from the PLS-SEM model. The map is divided into four quadrants based on the mean values of importance (0.209) and performance (76.61). The construct Perceived Knowledge (PK) is located in the quadrant with high importance and high performance, indicating a key strength of the model. The factor Perceived Usefulness (PU) falls into the quadrant with high importance but lower performance, identifying it as the most critical area for improvement. The construct Perceived Informedness (PI) is positioned in the quadrant with lower importance and higher performance. This suggests that although respondents perceive themselves as well-informed, this factor has a limited impact on the acceptance of Artificial Intelligence.

Finally, the construct Perceived Risk (RP) is located in the quadrant with low importance and low performance, indicating its marginal role in explaining the adoption of AI technologies.

The IPMA results provide (Table 1) an extended interpretation of the tested hypotheses by integrating both the statistical significance (PLS-SEM) and practical relevance (importance–performance).

- H1 (PI → AI in HE) was supported in the PLS-SEM model; however, IPMA reveals that despite relatively high performance, Perceived Informedness has only moderate importance. This indicates that increasing awareness alone may not substantially enhance AI adoption.

Table 1: IPMA results for AI in HE

Construct	Importance (Total Effect)	Performance (0–100)	Hypothesis	PLS-SEM Result	IPMA Interpretation
Perceived Knowledge (PK)	0,295	87,13	H2	Supported	Key strength (maintain)
Perceived Usefulness (PU)	0,220	65,96	H3	Supported	Priority for improvement
Perceived Informedness (PI)	0,189	77,00	H1	Supported	High performance, limited impact
Risk Perceived (RP)	0,133	76,34	H4	Not supported	Low priority factor

- H2 (PK → AI in HE) was strongly supported and confirmed as the most influential relationship. IPMA further shows that Perceived Knowledge combines high importance with high performance, identifying it as a well-established and stable determinant of AI acceptance.
- H3 (PU → AI in HE) was supported and identified as a significant predictor. Importantly, IPMA highlights Perceived Usefulness as the most critical improvement area, as it exhibits high importance but comparatively lower performance.
- H4 (RP → AI in HE) was not supported, which is consistent with IPMA results indicating low importance and low performance. This confirms that perceived risk does not represent a key barrier to AI adoption in the studied sample.

The combined interpretation of Partial Least Squares Structural Equation Modeling and Importance–Performance Map Analysis demonstrates that statistical significance alone is not sufficient for managerial decision-making. Although several relationships were confirmed, only selected constructs,particularly Perceived Usefulness (PU), offer substantial potential for improving AI adoption outcomes. The results clearly show that importance and performance do not necessarily align. While Perceived Knowledge (PK) is both highly important and well developed, Perceived Usefulness (PU) emerges as the only construct with a strong impact but insufficient performance, making it the primary target for intervention.

DISCUSSION

The aim of this study was to extend the understanding of Artificial Intelligence (AI) adoption in higher education by integrating Partial Least Squares Structural Equation Modeling (PLS-SEM) with Importance–Performance Map Analysis (IPMA). While PLS-SEM identified statistically significant relationships, IPMA added a practical dimension by linking these relationships to their relative importance and performance, thereby enabling more actionable interpretation. The findings are consistent with the Technology Acceptance Model (TAM), particularly regarding the central role of Perceived Usefulness (PU) as a key determinant of technology adoption. However, this study extends the traditional TAM perspective by demonstrating that perceived usefulness alone is insufficient unless it is supported by actual performance. The IPMA results reveal a critical gap: although PU has a strong impact on AI adoption, its performance remains relatively low. This suggests that students recognize the potential value of AI, but this value is not yet fully reflected in their learning experience.

A key contribution of this study lies in distinguishing between Perceived Knowledge (PK) and Perceived Usefulness (PU). While PK demonstrates both high importance and high performance, indicating that Generation Z students possess a well-developed understanding of AI technologies, PU represents a gap between potential and actual value. This finding suggests that knowledge does not automatically translate into meaningful use. Students may be capable of using AI tools, yet they do not necessarily perceive them as sufficiently beneficial in their academic work. The strong effect of PK is consistent with extended models such as UTAUT, where user competence plays a significant role. However, the results indicate that in digitally mature populations, knowledge is no longer a limiting factor. Instead, the key challenge lies in transforming this knowledge into perceived usefulness and practical value. This reflects a shift in adoption research from issues of access and awareness toward integration and effective use.

Perceived Risk (RP) was not found to have a significant effect on AI adoption, which contrasts with prior research emphasizing risk as a key barrier. This result can be explained by the characteristics of Generation Z, which tends to exhibit lower sensitivity to technological risks. The IPMA results further confirm that RP has low importance, suggesting that risk does not represent a priority for intervention. Similarly, Perceived Informedness (PI) shows relatively high performance but limited importance, indicating that being informed about AI does not necessarily lead to its adoption. This highlights a common limitation in adoption research: information alone is insufficient to drive behavior. In the context of AI, this suggests that strategies focused solely on awareness are unlikely to significantly increase adoption. From a theoretical perspective, the study contributes by integrating IPMA into technology adoption research and by identifying a critical gap between knowledge and usefulness. The findings suggest that the main barrier to AI adoption is not a lack of awareness, but the insufficient translation of AI capabilities into meaningful value. From a practical perspective, higher education institutions should move beyond awareness-building and focus on demonstrating the tangible benefits of AI in learning. This includes integrating AI tools into curricula, providing structured use cases, and supporting students in applying AI in real academic tasks. Overall, the study shows that the key challenge in AI adoption is not knowledge, but usefulness, and the ability to translate AI potential into meaningful educational outcomes.

Limitations

Despite its contributions, this study has several limitations that should be taken into account. The research is based on a relatively small sample of university students (n = 130), which may limit the generalizability of the findings. Furthermore, the study relies on self-reported data, which may be affected by Common Method Bias and social desirability effects. Respondents may overestimate their knowledge or provide answers that align with expectations rather than reflect their actual behavior. The research employs a cross-sectional design, which does not allow for the observation of changes in Artificial Intelligence adoption over time. Given the rapid development of AI technologies, user perceptions and behaviors may evolve dynamically. The model focuses on selected constructs derived from established technology acceptance frameworks, such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). Other potentially relevant factors, such as social influence, institutional support, or ethical considerations, were not included in the model. The study focuses on cognitive determinants and does not capture behavioral intention or actual usage behavior.

CONCLUSION

The aim of this study was to examine the determinants of AI adoption in higher education by combining PLS-SEM and IPMA. While the structural model identified statistically significant relationships, the IPMA approach provided deeper insights into their practical relevance. The findings confirm that Perceived Knowledge (PK) represents the strongest and most developed determinant of AI adoption among Generation Z students. At the same time, Perceived Usefulness (PU) emerged as the most critical factor for improvement, as it combines high importance with relatively lower performance.

This suggests that the key challenge in AI adoption is not a lack of awareness or knowledge, but rather the insufficient translation of AI capabilities into perceived practical value. Furthermore, the study shows that Perceived Informedness (PI), despite its relatively high level, does not significantly influence adoption, while Perceived Risk (RP) does not represent a major barrier. These findings indicate the need to shift attention away from information-based and risk-oriented approaches toward strategies that emphasize practical benefits and meaningful use of Artificial Intelligence in educational contexts. Overall, the study demonstrates that the combination of PLS-SEM and IPMA provides a more comprehensive understanding of technology adoption by linking statistical significance with practically actionable insights. Future research can build on this study in several directions. First, to enhance the generalizability of the findings, larger and more diverse samples should be employed. Comparative studies across different countries, educational systems, or age groups could provide a broader understanding of AI adoption patterns. Second, longitudinal research designs would enable the analysis of how perceptions of AI evolve over time, particularly in response to increasing exposure and technological advancement. Third, future studies could extend the model by incorporating additional variables such as social influence, facilitating conditions, trust, or perceived ethical concerns, thereby achieving a more comprehensive understanding of the factors influencing AI adoption. Fourth, qualitative approaches could complement quantitative findings by exploring how students actually use AI tools in their learning processes. Such insights could help explain the identified gap between Perceived Knowledge and Perceived Usefulness.

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