Vilnius University Press

Content lists are available at VilniusUniversity Press

Transformations In Business & Economics
2026, Vol. 25 No 2 (68), pp.55-82.

ISSN 1648–4460 | eISSN 2538-872X
https://doi.org/10.15388/Tibe.2026.25.2.20

Institutional resilience and AI adoption in a turbulent economic context: perceptions across stakeholders

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Annotation. Why should institutions consider stakeholders' perceived institutional resilience when developing AI deployment strategies? This study investigates how institutional resilience influences AI adoption intention, addressing the gap between capability-based management and stakeholder behavior intention, with an application to higher education. Using PLS-SEM and Necessary Condition Analysis in a multi-group design, we examine differences between faculty and students (Study 1) and across program delivery modes (Study 2). Results show that the effect of perceived institutional resilience on AI adoption intention is fully mediated by stakeholders' perceived value of AI. This mechanism is robust across groups and program delivery modes. However, while perceived AI value acts as a driver of adoption for both stakeholder groups, behavioral conditions differ: students require a minimum perceived AI value for high adoption intention, while faculty respond to perceived value in a more gradual, stepwise manner to achieve high levels of adoption. This underscores the need for value-based AI deployment strategies that account for institutional context and stakeholder constraints.

Keywords: artificial intelligence, institutional resilience, ai adoption, multi-group analysis, higher education.

JEL classification: O33, I23, M15, D83.

Introduction

Artificial Intelligence (AI) solutions are transforming the structure and processes of institutions. AI adoption rates have surged from 50% to 72% in recent years, driven by its ability to enhance efficiency and decision-making across a variety of business functions (McKinsey, 2024). Especially in tertiary institutions, this transformation has sparked debates about what is "right" and what is ethically or academically "wrong," particularly in relation to customization, automation, augmentation of tasks, and teacher-learner relationships. Given the complexity and rapid evolution of the technology, as well as resource constraints, faculty adoption challenges, and privacy concerns, research has emphasized the need for clear guidelines and policies to support AI adoption (Hazaimeh, Al-Ansi, 2024).

The process by which higher education institutions adopt AI—from teaching to administrative tasks—is influenced by perceived risks, performance expectations of the technology, and facilitating conditions (Chatterjee, Bhattacharjee, 2020). Both external and internal environmental factors play a crucial role,

Submitted on September 2025. Accepted on April 2026.

and partner support is highlighted as a necessary condition for successful adoption (Erdmann, Toro-Dupouy, 2025). Considering an institution's different stakeholders, AI acceptance is driven by a variety of perceived individual benefits and costs, making it essential to consider both students' and teaching staff's perspectives on perceived overall value delivery by AI technology and adoption intention. Research has shown that attitudes toward AI, digital competencies, and openness to experience are key drivers of adoption (Hazaimeh, Al-Ansi, 2024). This research stream has contributed to the development of AI acceptance theory in higher education, refining technology adoption models (Chatterjee, Bhattacharjee, 2020; Hazaimeh, Al-Ansi, 2024), emphasizing the role of digital and algorithmic competencies (De Obesso *et al.*, 2025; Núñez-Canal *et al.*, 2022), and the perceived benefits and value AI delivers to students and faculty (Baker, Smith, 2019; Nikolopoulou *et al.*, 2020).

The digital transformative processes within the firm—which we have lived with for the past few years—have been shown to improve organizational resilience, defined as the firm's ability to absorb disruptive surprises, provide situation-specific responses, and engage in transformative activities to survive and thrive (Zhang *et al.*, 2021). Mediated through explorative and exploitative innovations, the author's arguments rely on the dynamic capability perspective, which defines dynamic capabilities as "the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environment" (Teece *et al.*, 1997, p.516). Building on this view, recent research has emphasized the need for a strategic approach to AI adoption that fosters robust capabilities (Schwaeke *et al.*, 2025), requiring a clear understanding of the adoption process among the involved stakeholders.

Considering this management perspective alongside behavioral theories, stakeholders' perception of a firm's resilience may signal confidence in a successful transformation—particularly in the light of expected benefits for stakeholders—and indirectly influence their intention to adopt AI through stakeholders' assessment of the technology's value. However, the extent to which institutional resilience impacts consumers' value assessment of AI and its adoption in universities has so far not been explored. Understanding the underlying mechanisms—and their consistency or difference across stakeholder groups and modes of delivery (program types)—is relevant for developing AI deployment strategies that align with stakeholder perceptions and diverse learning environments.

The objectives of this research are threefold: (1) Compare stakeholder groups (faculty and students) with respect to perceived institutional resilience, AI value perception and AI adoption intention; (2) Examine how perceived institutional resilience influences AI adoption intention, with a focus on the mediating role of AI value perception and inter-group differences; (3) Assess how different modes of program delivery (in-person, hybrid, online and distance) shape AI adoption intention.

We build on the reasoning of stage-wise organizational resilience (Duchek, 2020) and technology adoption mediated through perceived value (Kim *et al.*, 2007). We set up a structural model and conducted two studies to analyze the role of perceived institutional resilience in AI adoption intention, taking into account inter-group differences in higher education environments and the learning mode. Study 1 examines differences between students and faculty, while Study 2 explores variations across learning modes.

In line with previous literature, we employ partial least squares structural equation modeling (PLS-SEM) to explore the underlying mechanism (e.g. AlGerafi *et al.*, 2023; Chatterjee, Bhattacharjee, 2020; Zhang *et al.*, 2021), complemented by Necessary Condition Analysis (NCA) to identify critical minimum levels of adoption drivers that may act as a constraint (Richter *et al.*, 2020; 2022; 2023).

The results reveal that the impact of perceived institutional resilience on AI adoption intention is fully mediated by stakeholders' AI value perception, a mechanism that remains robust across both faculty and student populations as well as across different program delivery modes. Notably, there are significant differences in perceptions of institutional resilience between stakeholder groups; however, despite initial expectations of role-based differences, students and faculty show no significant differences in their mean levels of AI value perception or adoption intention. Instead, we find that their value-based behavioral paths differ, as they face different constraints. Students show a clear threshold-based adoption pattern, where reaching a minimum perceived AI value is required for high adoption intention to become feasible. In contrast, for faculty, AI value shows a stepwise relation with adoption intention, indicating an incremental constraining pattern rather than a threshold effect. Consequently, these findings suggest that institutions should move beyond a one-size-fits-all implementation approach toward value-based AI deployment strategies that leverage perceived institutional resilience to meet stakeholders' value assessments, while addressing the specific motivations and contextual constraints unique to each group and delivery mode.

1. Theoretical Framework: Inter-Group Differences in AI Value Perception and Adoption

AI has become a transformative force in higher education, offering tools that enhance teaching, learning, and administrative functions (Bates *et al*., 2020). However, its adoption is not uniform across stakeholders (Agha-Mir-Salim *et al*., 2022; Karran *et al*., 2024). Faculty members often approach AI with caution due to concerns about pedagogical integrity and over-reliance on technology, while students tend to embrace AI for its perceived utility in improving academic performance and efficiency. These contrasting perspectives reflect broader value-based inter-group differences that warrant systematic exploration.

To explore these differences, we build on perceived value theory (Zeithaml, 1988). The perceived value of products or services results from a trade-off between perceived benefits and sacrifices, which determines the overall value assessment (an approach analogous to perceived value considerations in other contexts), and a unidimensional approach is recommended when studying the impact of value on other constructs, like satisfaction or behavioral intention (Alves, 2011). Applying a similar logic to technology adoption, perceived value serves as the principal determinant of behavioral intention, that is, adoption intention is more likely to be high when the consumer's overall perception of value is high (Kim *et al*., 2007). However, it is important to note that value is fundamentally context-specific, depending on the specific situation or set of circumstances facing the decision-maker (Sheth *et al*., 1991). Finally, regarding the adoption of AI technology in a university context and its antecedents, studies emphasize personalization, efficiency, task automation, and feedback and support as key benefits that drive acceptance (Zawacki-Richter *et al*., 2019). Specifically, student acceptance and expected use of technology are significantly influenced by the expected benefits of personalized academic support balanced against their perceived control over personal data (Ifenthaler, Schumacher, 2016).

However, the emphasis on particular value drivers varies across user groups. Instructors, for example, recognize not only the efficiency of automating administrative tasks but also AI's potential to support formative assessment and provide timely feedback (Erdmann, Toro-Dupouy, 2025). For students, the perceived benefit lies in access to 24/7 academic support and adaptive learning resources (Baker, Smith, 2019). However, these perceptions are influenced by levels of digital literacy and institutional support systems (Smutny, Schreiberova, 2020). Faculty recognize the potential of AI to enhance pedagogical practices through personalized learning, adaptive assessments, and data-driven decision-making. For instance, Zawacki-Richter *et al*. (2019) found that faculty view AI as a tool for increasing student engagement and improving learning outcomes. Similarly, Anuyahong *et al*. (2023) found that while educators recognize AI's potential to provide valuable insights into student learning and personalized feedback, their perspectives are tempered by skepticism regarding algorithmic bias and the potential loss of human connection in instruction. Concerns include the potential erosion of academic rigor, ethical issues surrounding data privacy, and the risk of over-reliance on AI tools (Abulibdeh *et al*., 2024; Chan, Tsi, 2023; Kumar *et al*., 2024). Faculty with more years of teaching experience or those from non-technical disciplines are particularly resistant to adopting AI technologies due to limited familiarity and perceived incompatibility with traditional teaching methods (Bates *et al*., 2020; Hazaimeh, Al-Ansi, 2024). Wang *et al*. (2024) emphasized that exposure to AI systems significantly influences faculty openness to adoption, suggesting that targeted training programs could mitigate resistance.

In contrast, students generally exhibit a more favorable attitude toward AI than faculty. They perceive generative artificial intelligence (GenAI) tools such as ChatGPT as user-friendly and effective for enhancing academic performance (Chan, Tsi, 2023; Lavidas *et al*., 2024; Pisica *et al*., 2024; Polyportis, Pahos, 2024). STEM students, in particular, are enthusiastic about AI's potential to simplify complex tasks and facilitate innovative problem-solving approaches. However, students also have some reservations. Ethical concerns regarding AI use in academia persist, with some expressing uncertainty about the boundaries of acceptable AI-assisted work. A study comparing student and instructor perceptions of academic dishonesty found that students were more likely to view collaborations involving AI as ethically ambiguous (Gallagher, Wagner, 2024). This divergence in perspectives highlights the need for clear guidelines on acceptable AI use in academic settings, ensuring that both faculty and students can navigate the evolving technological landscape with confidence. Students perceive several specific benefits of GenAI in their educational experiences (Chan, 2023). One of the key advantages is its ability to provide personalized and immediate learning support. GenAI can function as a virtual tutor, offering tailored assistance and responding promptly to students' questions, particularly when they encounter difficulties with assignments. Additionally, students find GenAI invaluable for writing and brainstorming. It helps them generate ideas and offers constructive feedback on their writing, which is especially beneficial for non-native English speakers who may face challenges in articulating their thoughts (Atalas, 2023; Berg, 2023). Moreover, GenAI technologies significantly enhance research and analysis. They assist students in generating ideas, synthesizing information, and summarizing extensive texts, resulting in a more efficient research process (Berg, 2023). In fields that require visual and audio elements, tools like text-to-image generators can greatly enrich the learning experience, making complex concepts more accessible and engaging, particularly in technical and artistic disciplines (Dehouche, Dehouche, 2023).

The differences in value perception and adoption between faculty and students highlight the need for tailored strategies when implementing AI technologies in educational settings to address their unique concerns and expectations effectively. As noted by Chan and Tsi (2023), concerns from faculty regarding the implications of AI tools on students' holistic competency development underscore the necessity for understanding how different user groups view these technologies. Differences in perspectives suggest that faculty and students may require different approaches to integrating AI based on their unique perceptions.

Beyond these individual perceptions, institutional resilience and organizational readiness are decisive in shaping technology adoption in any institution. Resilience refers not only to recovery from crises but is a meta-capability that allows an organization to anticipate potential threats, cope effectively, and adapt to changing conditions (Duchek, 2020); incorporating proactive strategies and structural adaptability that foster continuity and innovation during uncertain times (Williams *et al*., 2017). Resilience can be considered as a stage-wise process, where an institution's resilience level is determined by its ability to master three successive stages (anticipation, coping, and adaptation), and resilience levels require the combined development of all three phases (Duchek, 2020). Organizational readiness involves both technical infrastructure and human resources—crucial elements for digital transformation (Almarzooq *et al*., 2020; Weiner, 2009). Institutions that promote a culture of innovation, offer professional development, and demonstrate strong leadership are more likely to implement AI tools successfully (Bond *et al*., 2021). The COVID-19 pandemic has further emphasized resilience, as institutions with prior investments in digital platforms adapted more smoothly to remote and hybrid learning models (Hodges *et al*., 2020). Adoption patterns differ significantly across stakeholder groups. Faculty members might be hesitant to adopt AI due to perceived threats to their pedagogical independence or doubts about reliability (Selwyn, 2019). Conversely, students often show more openness to AI-enhanced learning, especially when it matches their digital habits and expectations for on-demand access (Luckin *et al*., 2016). Moreover, differences in the incentives and process of AI adoption are also expected across instructional formats. Online learners tend to see greater benefits from AI integration, valuing features like real-time feedback and personalized learning pathways (Nikolopoulou *et al*., 2020). In contrast, in-person learners may prioritize human interaction and see AI tools as supplementary rather than essential. Hybrid learners often navigate both views, depending on the balance between synchronous and asynchronous elements in their courses (Rapanta *et al*., 2020). Demographic factors like age, gender, academic discipline, and prior experience with educational technology influence attitudes toward adoption (Bower, 2019). Faculty in STEM fields may be more inclined to adopt AI than those in the humanities, and younger faculty and students generally have more positive attitudes toward experimenting with technology (Algerafi *et al*., 2023; Chan, Tsi, 2023; Bates *et al*., 2020).

2. Research Model Development

2.1 Factors Influencing Inter-Group Differences in AI Adoption

Perceptions of AI vary by academic field, with STEM faculty and students more inclined to adopt AI tools than those in the humanities or social sciences (Bates *et al*., 2020; Algerafi *et al*., 2023). This disparity reflects differences in technological familiarity and the extent to which AI is seen as useful in specific fields. Also, younger faculty members are generally more receptive to AI integration than their older colleagues. This generational divide is partly attributed to differing levels of exposure to digital technologies during formative years. While students focus on the utility of AI for academic tasks, faculty prioritize its alignment with pedagogical goals. Faculty concerns about over-reliance on AI contrast sharply with student enthusiasm for its convenience, underscoring the need for balanced adoption strategies.

Research by Hazaimeh and Al-Ansi (2024) identifies several key factors that influence AI acceptance among teaching staff and students. One crucial factor is attitudes, meaning a person's general stance toward AI, which strongly influences their willingness to adopt it (AlGerafi *et al*., 2023; Chatterjee, Bhattacharjee, 2020). Additionally, digital competencies play a vital role, as users with higher levels of digital skills and proficiency are more comfortable and capable of utilizing AI tools effectively (Hazaimeh , Al-Ansi, 2024; Abulibdeh *et al*., 2024), thereby enhancing learning outcomes (Nuñez-Canal *et al*., 2022). Another important aspect is openness to experience; individuals who are more receptive to new technologies and experiences are generally more inclined to integrate AI into their educational practices (Hazaimeh, Al-Ansi, 2024). Furthermore, the perceived benefits of AI, such as personalized learning, efficient feedback, and support for diverse learning needs, positively impact its acceptance. Together, these factors provide valuable insights into how teaching staff and students perceive and engage with AI technologies in higher education settings (Hazaimeh, Al-Ansi, 2024).

AlGerafi *et al*. (2023) examined the key factors influencing students' intentions to adopt AI-based robots in higher education, drawing on the modified Technology Acceptance Model. One of the primary determinants is Perceived Usefulness, which refers to students' belief that AI-based robots can enhance their learning experience and improve educational outcomes. The more students perceive these technologies as beneficial, the more likely they are to adopt them. Similarly, Perceived Ease of Use plays a crucial role; if students find AI-based robots intuitive and user-friendly, their willingness to integrate them into their learning process increases. Moreover, social norm effects suggest that when students observe positive acceptance of these technologies within their academic environment, they are more likely to adopt them. Additionally, self-efficacy, or students' confidence in their ability to use AI-based robots effectively, significantly impacts their likelihood of adoption. Those who feel capable of navigating and utilizing these tools are more willing to embrace them. AI is transforming higher education by offering tools that improve learning outcomes, simplify academic tasks, and promote creativity. Applications like ChatGPT have become prevalent in academic environments, allowing students to generate ideas, enhance their writing skills, and obtain personalized learning support (Polyportis, Pahos, 2024). However, it is essential to understand the factors that influence students' intentions to adopt these technologies in order to optimize their use and address any potential challenges. Performance expectancy plays a significant role in the adoption of AI tools among students, as it refers to their belief that these technologies will enhance their academic performance (Polyportis, Pahos, 2024). For instance, ChatGPT is often valued for its ability to improve productivity and learning outcomes (Lavidas *et al*., 2024; Polyportis, Pahos, 2024). Closely related to performance expectancy is effort expectancy, which concerns the ease of use associated with AI technologies. Tools like ChatGPT are frequently praised for their user-friendly interfaces, requiring minimal learning effort for effective operation. This perceived ease of use positively influences students' attitudes toward adopting AI (Polyportis, Pahos, 2024).

Beyond individual perceptions of performance and effort, social influence also plays a key role in shaping AI adoption intentions. Lavidas *et al*. (2024) suggest that institutional endorsements and encouragement from others (peers, educators etc.) significantly impacts adoption, as social norms promoting AI usage can enhance behavioral intentions. Furthermore, institutional validation helps legitimize these tools within academic settings, increasing students' receptiveness to their use. In addition to social influence, trust is another crucial factor in fostering the adoption of AI systems (Asan *et al*., 2020). Positive experiences with tools like ChatGPT contribute to building user trust, reinforcing continued engagement. Conversely, concerns regarding data privacy and potential misuse can undermine trust, ultimately reducing adoption rates.

Finally, habit formation emerges as a strong predictor of continued AI use (Lavidas *et al*., 2024). Individuals who engage repeatedly with ChatGPT tend to develop habitual usage patterns, making them more likely to integrate these tools into their academic workflows, regardless of external challenges (Polyportis, Pahos, 2024). As a result, fostering positive initial experiences and minimizing barriers to use can encourage sustained engagement with AI technologies.

Research has shown that students and faculty see the value of AI in education differently because of their different roles, expectations, and experiences in higher education. While students often emphasize AI's ability to support personalized learning, boost academic productivity, and provide quick feedback (Chan, 2023; Polyportis, Pahos, 2024), faculty members tend to judge AI based on how well it fits pedagogically, its ethical implications, and the integrity of assessment methods (Karran *et al*., 2024;

Selwyn, 2019). This difference is reinforced by findings indicating that students associate AI tools like ChatGPT with better academic results and idea generation (Atalas, 2023; Berg, 2023), while faculty maintain a more critical perspective, balancing the benefits of automation with educational standards (Zawacki-Richter *et al*., 2019). These differing value judgments reflect broader attitudinal and disciplinary gaps in AI acceptance, further supporting the need to explore stakeholder-specific perceptions of AI's value. Taking it all together, these role-based differences in priorities related to AI lead us to hypothesize that students and faculty differ significantly in their overall perceptions of the value of AI technology in higher education.

Hypothesis 1a: Students and faculty differ in their overall assessment of AI's value.

Differences in AI adoption between students and faculty align with the broader literature on technology acceptance, which indicates that generational exposure, digital literacy, and role-based expectations influence adoption behavior (Chan, Tsi, 2023). Students, especially in digitally immersive environments or STEM fields, tend to show more enthusiasm for integrating AI tools into their academic routines due to familiarity and perceived relevance (Polyportis, Pahos, 2024). Conversely, faculty—particularly those in humanities or with more years of teaching experience—often express hesitancy stemming from concerns about reliability, data privacy, and the potential erosion of traditional pedagogical practices (Anuyahong *et al*., 2023). The Unified Theory of Acceptance and Use of Technology also indicates that social influence and facilitating conditions vary significantly between these groups (Venkatesh, Bala, 2008), resulting in different behavioral intentions, and these differences should be considered in institutional strategies. Hence, we hypothesize that inter-group differences exist in AI adoption intention within the higher education context.

Hypothesis 1b: Students and faculty differ in their intention to adopt AI.

The positive connection between perceived value and intention to adopt new technologies is well supported by the large literature on technology acceptance models (TAM) and value adoption models (VAM). In TAM frameworks, perceived usefulness is a key factor influencing the intention to use new technology (Davis, 1989; Venkatesh, Bala, 2008). In the context of AI in education, students and faculty are more likely to adopt tools they see as improving learning outcomes, streamlining administration, or saving time (Chan, Tsi, 2023; Ifenthaler, Schumacher, 2016). Since users of technology base their decisions on their overall evaluation of the technology's potential payoff, the overall assessment becomes a crucial determinant for adoption intention (Kim *et al*., 2007). Empirical studies also confirm that value perceptions—such as return on effort, time, or cost—significantly influence attitudes toward GenAI tools like ChatGPT (Polyportis, Pahos, 2024; Lavidas *et al*., 2024), and attitudes are well-established antecedents of behavior intention (Ajzen, 1991; Davis, 1989). Reinforcing this perspective, Chatterjee and Bhattacharjee (2020) show that within the higher education sector, a stakeholder's attitude acts as a decisive mediator between technological expectations and the behavioral intention to adopt AI. From a value perspective, value-based adoption models emphasize the role of overall value perception as a mediator between benefits and costs within a given technological setting and adoption intention (Kim *et al*., 2007). In this context, stakeholders' value perception of AI technology in higher education institutions is expected to drive their adoption intention, leading to the following hypothesis:

Hypothesis 1c: Stakeholders' overall value assessment positively influences their intention to adopt AI.

2.2 The Role of Perceived Institutional Resilience in AI Adoption

AI has become a transformative force across industries, offering opportunities for efficiency, innovation, and resilience. However, the adoption of AI is not merely a technological decision but is deeply embedded in institutional contexts. Perceived institutional strength shapes trust, which is a critical factor influencing AI adoption (Wong *et al.*, 2024). When it comes to the adoption of GenAI, institutional readiness is critical because the technology represents a paradigm shift in how organizations operate, and in this context, the concept of dynamic capabilities and resilience becomes paramount.

Dynamic capabilities are understood as the ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments (Teece *et al.*, 1997), a framework that serves as a foundation for understanding the meta-capability of resilience (Duchek, 2020). Accordingly, organizational resilience refers to an organization's ability to adapt and transform in the face of challenges while maintaining its core functions and objectives (Barasa *et al.*, 2018).

Several key dimensions underpin institutional resilience and influence AI adoption. Regulatory compliance plays a crucial role, ensuring that organizations adhere to evolving legal frameworks that safeguard trust and legitimacy in AI implementation (Barasa *et al.*, 2018). This compliance fosters confidence among stakeholders and mitigates ethical and legal risks (Vishwakarma *et al.*, 2024). Equally important is organizational culture; institutions that promote innovation and continuous learning are more likely to integrate AI effectively. A culture that encourages curiosity, experimentation, and tolerance towards failure enhances an organization's capacity to harness AI's potential (Schintler, McNeely, 2022). Additionally, technological infrastructure is a fundamental enabler of AI adoption. Robust IT systems provide the necessary foundation for seamless AI implementation, ensuring that organizations have the tools and resources to support advanced technologies (Grimmelikhuijsen, Tangi, 2024). Leadership adaptability further strengthens institutional resilience, as emotionally intelligent leaders can navigate the complexities of change, inspire teams, and foster a culture of collaboration that facilitates AI adoption (Barasa *et al.*, 2018; Schintler, McNeely, 2022).

The interplay between institutional resilience and AI adoption is particularly evident in how organizations approach technological preparedness (Barasa *et al.*, 2018; Kanbach *et al.*, 2024), cultural readiness (Barasa *et al.*, 2018; Schintler, McNeely, 2022), and risk management (Barasa *et al.*, 2018; Duchek, 2020). Resilient organizations are more willing to embrace AI despite inherent risks, as regulatory frameworks provide transparency and accountability, reinforcing institutional confidence. Cultural readiness also plays a crucial role; organizations with adaptive cultures are better equipped to address ethical concerns and operational challenges that arise during AI implementation (Abulibdeh *et al.*, 2024). Leadership remains a pivotal factor, as leaders who demonstrate adaptability and high emotional intelligence can navigate uncertainties, build stakeholder trust, and foster collaborative decision-making (Coronado-Maldonado, Benítez-Márquez, 2023). Finally, technological preparedness serves as the foundation of institutional resilience. Organizations with well-established IT infrastructures not only view themselves as capable of adopting AI effectively but also strengthen their overall resilience in the face of technological change (Grimmelikhuijsen, Tangi, 2024). By integrating these elements, institutions can position themselves to leverage AI successfully while maintaining adaptability and stability in an evolving digital landscape.

However, individual perceptions of this resilience may not be uniform across stakeholder groups. The relationship with the stakeholder influences how resilience is perceived and the interpretation by external observers is contextual (Liu, Yin, 2020). This aspect, that resilience is relational, is also highlighted by McKnight and Linnenluecke (2016), depending on how the different groups are prioritized and supported during turbulent times. That is, given the different relationship of the institution with faculty members and with students, perceived institutional resilience may differ systematically between faculty and students, so that we hypothesize as follows:

Hypothesis 2a: Students and faculty differ in their perceived institutional resilience.

Institutional resilience encourages an environment that supports positive perceptions of AI by signaling stability, adaptability, and long-term strategic thinking (Barasa *et al*., 2018; Duchek, 2020; Schintler, McNeely, 2022). When stakeholders see their institution as resilient, they are more likely to assign greater value to AI initiatives, viewing them as part of a broader adaptive capacity rather than as reactive or experimental efforts (Schintler, McNeely, 2022). This role of value perception aligns with capability-based perspectives, which highlight that organizational readiness and institutional confidence improve stakeholders' evaluation of innovation benefits (Teece *et al*., 1997; Zhang *et al*., 2021). As a result, institutions seen as capable of withstanding disruptions are more likely to build trust in new technologies, thereby indirectly increasing adoption intentions through higher AI value perceptions. Hence, perceived institutional resilience is understood as an antecedent of users' overall value assessment and adoption intention of AI, and we hypothesize as follows:

Hypothesis 2b: Perceived institutional resilience has a positive effect on AI adoption intention, mediated by stakeholders' value perception of AI technology.

Beyond its influence through perceived value, institutional resilience also independently contributes to AI adoption by strengthening stakeholders' confidence in change management processes and long-term digital integration (Barasa *et al*., 2018; Schwaeke *et al*., 2025). Institutions that show agility, leadership adaptability, and strong technological infrastructure demonstrate readiness for digital transformation, which positively influences behavioral intentions toward adopting AI (Grimmelikhuijsen, Tangi, 2024). Resilience, therefore, serves not only as a background for value perception but also as a direct antecedent of the AI adoption environment. This is especially important in turbulent environments, where resilience indicates organizational commitment to innovation, stability, and ethical AI deployment, reducing uncertainty and encouraging proactive engagement by stakeholders. Therefore, we set up the following hypothesis:

Hypothesis 2c: Perceived institutional resilience has a direct positive effect on AI adoption intention.

2.3 The Role of Modes of Delivery—In-Person, Hybrid, Online or Distance—in AI Value Perception and Adoption

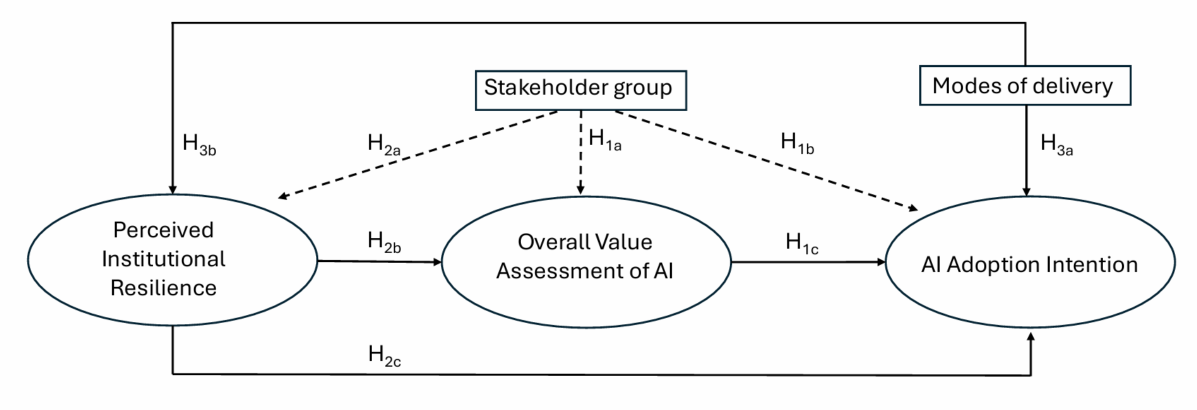
AI has emerged as a transformative force across industries, with its adoption accelerating globally. However, the mode through which AI-related programs are delivered—educational or organizational—plays a critical role in shaping stakeholders' perceptions of their value and their willingness to adopt it.

Different modes of AI-related education influence adoption by affecting accessibility, engagement, and perceived value. In-person programs enhance AI's perceived utility by enabling direct interaction with instructors who can demystify complex concepts. For example, vocational training programs focusing on AI technologies have successfully cultivated innovation skills through hands-on activities. However, despite their effectiveness, in-person programs are often limited in reach due to logistical constraints. On the other hand, online programs expand accessibility by making AI education available to a wider audience. These platforms, particularly those equipped with AI-driven analytics, can identify at-risk learners early and improve learning outcomes (Kumar *et al*., 2024). However, without sufficient support or engagement mechanisms, online programs risk being perceived as impersonal, which can negatively impact learners' motivation and perceived value. Hybrid programs offer a balanced approach by integrating human interaction with AI-driven personalization. For instance, hybrid learning environments use predictive analytics to tailor content while maintaining opportunities for face-to-face collaboration (Kumar *et al*., 2024). By combining the strengths of both in-person and online modalities, hybrid programs enhance the perceived utility of AI tools, demonstrating their practical applications in real-world settings and fostering greater acceptance among stakeholders. However, the success of this approach may depend on the seamlessness of integration.

Modes of delivery are expected to affect AI adoption intentions because of variations in technological exposure, instructional methods, and student engagement (Kumar *et al*., 2024). Online learners are more immersed in digital environments and therefore more likely to see AI tools as essential and helpful for their academic success (Nikolopoulou *et al*., 2020). Conversely, in-person program participants often depend on traditional face-to-face instruction and may view AI as additional rather than central (Rapanta *et al*., 2020). Hybrid programs, depending on how they balance synchronous and asynchronous components, imply different levels of technological exposure. Additionally, students in resilient online programs report higher trust in AI tools due to robust digital infrastructure and support systems (Bond *et al*., 2021), which may also shape their perception of institutional resilience. Thus, the type of program (learning mode) is expected to influence users' adoption intention, and we hypothesize as follows:

Hypothesis 3a: The mode of delivery affects AI adoption intention.

Hypothesis 3b: The mode of delivery affects perceived institutional resilience.



Source: own elaboration.

Figure 1. **Research Model on the Role of Perceived Institutional Resilience on AI Adoption by Multi-Groups**

Figure 1 summarizes the developed hypotheses on the underlying mechanism and inter-group differences in AI adoption intention in higher education institutions.

3. Data and Methodology

An online questionnaire was designed with the focus of measuring perceived institutional resilience, respondents' value perception of AI, and AI adoption intention, as well as including additional questions on respondents' profiles and collecting information for a business report.

The measurement scales were built using validated 5-point Likert scales, and all scales were translated into Spanish (a pre-test was conducted). Perceived resilience of higher education institutions is measured by adapting the resilience scale from Parker and Ameen (2018), used by Zhang *et al*. (2021) in the context of digital transformation. The measurement of perceived AI value is adapted from Kim *et al*. (2007), which has been applied in studies on technology adoption for recent disruptive technologies. Intention to adopt AI is measured following Chatterjee and Bhattacharjee (2020). *Table A1* in the Appendix provides the variables and measurement scales.

Data for this study were collected through online questionnaires from two distinct samples representing different stakeholder groups in higher education institutions across Spain and Latin America. The online survey was conducted with the approval of the participating institutions. Participation was voluntary, informed consent was obtained, and responses were collected anonymously. Sample 1, comprising students, was gathered in two waves between April and June 2024 and October and December 2024, resulting in N_1 = 189 valid observations. Sample 2, consisting of professors, administrative staff, and executives (hereafter "faculty"), was collected between July and August 2023, yielding N_2 = 156 valid observations.[i] The two samples were combined into a single dataset by appending the variables.

The study classifies participants based on two segmentation criteria: stakeholder type and program type (mode of delivery). In terms of stakeholder type, the sample consists of 189 students (55%) and 156 individuals (45%), who are professors, administrative staff, or executives at higher education institutions. Regarding program type, 65% of respondents were enrolled in programs that included some form of online delivery, while 35% were enrolled in fully in-person programs. We distinguish between online, hybrid, in-person, and distance learning modalities. However, given the very small number of cases in the pure distance learning category, this modality was combined with online learning for statistical analysis.

Second, we build a structural model to study the effect of resilience on AI perception, mediated through stakeholders' AI value perception (*Figure 1*). For the analysis, we use partial least squares structural equation modeling (PLS-SEM). Following Hair *et al*. (2021), this type of path modeling of the respective relationships between latent constructs in our hypothesis (perceived institutional resilience, overall value assessment of AI, AI adoption intention), provides insights into behavioral mechanisms. The exploratory nature of this approach is particularly relevant for managerial purposes, as it allows the underlying variability in latent outcomes to be explained while remaining efficient even with small sample sizes. The model is estimated in R using the freely available software packages SEMinR (Ray *et al*., 2021) and semPLS (Monecke, Leisch, 2013), as suggested in the workbook by Hair *et al*. (2021). We use multi-group analysis (MGA) to assess group differences in structural path coefficients. While the PLS-SEM approach allows us to assess mediation relationships between constructs, as specified in the hypotheses, it does not capture contextual factors or constraints that may trigger adoption-related behavior. To address this limitation, we complement the PLS-SEM analysis with a Necessary Condition Analysis, following Richter *et al*. (2020, 2022, 2023), which enables us to identify potential behavioral constraints within the examined mechanism through which institutional resilience influences AI adoption in higher education.

4. Analysis of Results

First, we examined and prepared the two datasets for analysis, merged them, and assessed the reflective measurement model, evaluating its validity and reliability for the full sample. Subsequently, we conducted a descriptive between-group analysis, comparing students and faculty across all three variables. Finally, we estimated the structural model for the full sample and separately for each group and conducted a Necessary Condition Analysis to identify potential constraints underlying AI adoption.

4.1 Model Measurement Validity

First, we consider the relationship between the three concepts and corresponding indicators for the full sample. *Table 1* provides the validity and reliability analysis. Considering the validity analysis for the items, the loadings indicate how much of the variability of each of the concepts is explained by the observed survey responses to each corresponding question. All but one loading exceed the recommended threshold of 0.708 (Carmines, Zeller, 1979). The loading of PV1 in the admin sample is slightly below the threshold, therefore, the model was estimated first without this item and its inclusion was examined in a sensitivity check. For the validity analysis for the constructs, we report Cronbach's alpha and rhoA. All alpha values are larger than the critical threshold of 0.70 and even exceed the desired level of 0.9 for consolidated research (Nunnally, Bernstein, 1994), and also rhoA values are above the acceptable thresholds of 0.7 and even above 0.9 (Dijkstra, Henseler, 2015). To assess convergent validity, we report the average variance extracted (AVE). All constructs show strong convergent validity with values higher than 0.75 (Hair *et al*., 2021). With respect to discriminant validity, the cross-loadings were examined, and we provide the Heterotrait–Monotrait ratios (HTMT). The resulting average correlation ratios show that all indicators load to a greater extent on their respective construct than on others, below the 0.90 threshold (Hair *et al*., 2021).

Table 1. Measurement Model: Validity and reliability analysis

Construct	Items	Loadings	Validity constructs			HTMT		
			alpha	rhoA	AVE	PV	ITA	RES
PV	PV1	0.686						
	PV2	0.902						
	PV3	0.920						
	PV4	0.924	0.916	0.931	0.746	1.000	0.810	0.368
ITA	ITA1	0.932						
	ITA2	0.887						
	ITA3	0.822						
	ITA4	0.944	0.943	0.946	0.806	0.810	1.000	0.238
RES	RES1	0.822						
	RES2	0.851						
	RES3	0.922						
	RES4	1.001	0.947	0.951	0.813	0.368	0.238	1.000

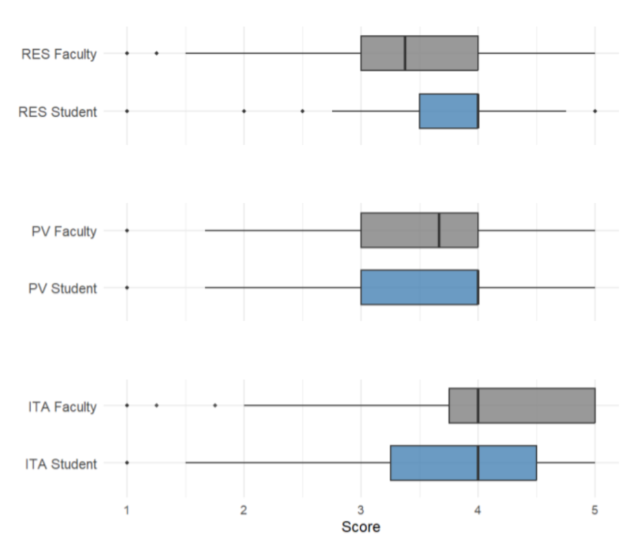
Source: own elaboration.

Additionally, we assess potential multicollinearity among the predictors in the model by reporting the variance inflation factors (VIF). The VIF values for perceived value and institutional resilience are both 1.129, which are below 3. Therefore, we rule out any multicollinearity concerns (Hair *et al*., 2021).

4.2 Study 1: Stakeholder Differences and Behavioral Constraints in AI Adoption

Table 2 presents the descriptive statistics and boxplots for a visual comparison of the distribution of resilience, AI value perception, and adoption intention between faculty and students. To test for significant differences in mean values between these two groups, we employ a t-test, allowing for a straightforward comparison of the composite scores for students and faculty.

Table 2. Inter-group comparison of Perceived Institutional Resilience, AI Value Perception, and AI Adoption Intention

Study 1	**Mean**	**Std.dev**	**Inter-group comparison**	**t-test** (p-value)
RES				4.74 (< 0.001)
Full sample	3.628	0.869		
Faculty	3.388	0.894		
Student	3.825	0.798		
PV				1.27 (0.205)
Full sample	3.641	0.844		
Faculty	3.577	0.854		
Students	3.693	0.834		
ITA				−1.83 (0.069)
Full sample	3.913	0.896		
Faculty	4.010	0.909		
Students	3.833	0.879		

Source: Own elaboration. ITA = AI Adoption Intention; PV = AI Value Perception (Overall Value Assessment of AI); RES = Perceived Institutional Resilience

The results indicate that perceived institutional resilience differs significantly between groups (H_{2a}), with students reporting a higher average resilience score, while faculty report a lower score. Additionally, faculty exhibit greater variability in their resilience assessments.

Perceived AI value is statistically equivalent across the two groups. Likewise, we cannot reject the statistical equality of mean AI adoption intention between students and faculty, even though faculty members exhibit higher individual scores. That is, despite the different motivations highlighted in the literature, the overall assessment of AI and the intention to adopt it are similar across groups (thus, H_{1a} and H_{1b} are not supported).

For exploratory purposes, to examine the relationship between institutional resilience and AI value perception, as well as AI adoption intention, we first construct a contingency table (Appendix *Figure* A1). The distribution suggests that at low levels of perceived institutional resilience, both AI value perception and AI adoption intention tend to be low. The concentration of responses is at moderate to high levels of resilience, where AI value perception and adoption intention are also higher. Visual inspection suggests a positive association between institutional resilience and stakeholders' perceptions of AI value and their intention to adopt AI.

Considering inter-group differences, we explore the distribution of AI adoption intention across different respondent groups at varying levels of perceived resilience, using boxplots for visualization (*Appendix*, *Figure* A2). For students, visual inspection of the boxplots suggests a positive relationship between the level of institutional resilience and students' intention to adopt AI; however, this should be interpreted with caution, since the distribution of students at low levels of perceived resilience is sparse. For faculty, the average score for AI adoption intention remains high and stable at very low to moderate levels of resilience. However, at high levels of resilience, adoption intention increases further, a pattern that is also observed among the student group. Furthermore, the variance in AI adoption intention is lowest at moderate levels of resilience. This finding, though requiring cautious interpretation, suggests that institutional resilience may function as a stabilizing factor in stakeholders' AI adoption intentions, reducing variability in their responses.

To analyze this relationship, we estimate the structural model (*Figure 1*), first for the full sample and subsequently for the subsamples. The estimated path coefficients for the full sample are provided in *Table 3* for the whole sample, and bootstrap resampling (N=500) is used to calculate the t-statistic and confidence intervals for all estimates. The R^2 value indicates that the model accounts for 66.2% of the overall variance in AI adoption intention in higher education, which, given the relatively young research context, is considered a large effect size.

Table 3: Estimated path coefficients (full sample)

Full sample	Path coefficient	T Stat	CI
PV → ITA	0.832	28.667	[0.769; 0.886]
RES → ITA	-0.056	-1.336	[-0.141; 0.023]
RES → PV	0.359	5.306	[0.219; 0.482]
R^2	0.662		

Source: own elaboration.

The AI value perception has a significant positive effect on AI adoption intention (H_{1c}). The effect of perceived institutional resilience on AI adoption is fully mediated by stakeholders' AI value perception (H_{2b}). That is, statistical analysis fails to support a direct relationship between perceived institutional resilience and AI adoption intention (not supporting H_{2c}).

Table 4: Estimated path coefficients (MGA by stakeholder group)

Full sample	β_S	T Stat	CI	β_F	T Stat	CI	$\beta_S - \beta_S$ (SE)
	Faculty			Students			
PV → ITA	0.808	22.598	[0.741; 0.878]	0.842	25.183	[0.766; 0.898]	0.034 (0.049)
RES → ITA	-0.052	-0.844	[-0.189; 0.053]	0.070	1.519	[-0.017; 0.162]	0.122 (0.077)
RES → PV	0.290	2.890	[0.100; 0.480]	0.350	3.431	[0.139; 0.529]	0.060 (0.143)
R^2	0.632			0.756			

Source: own elaboration.

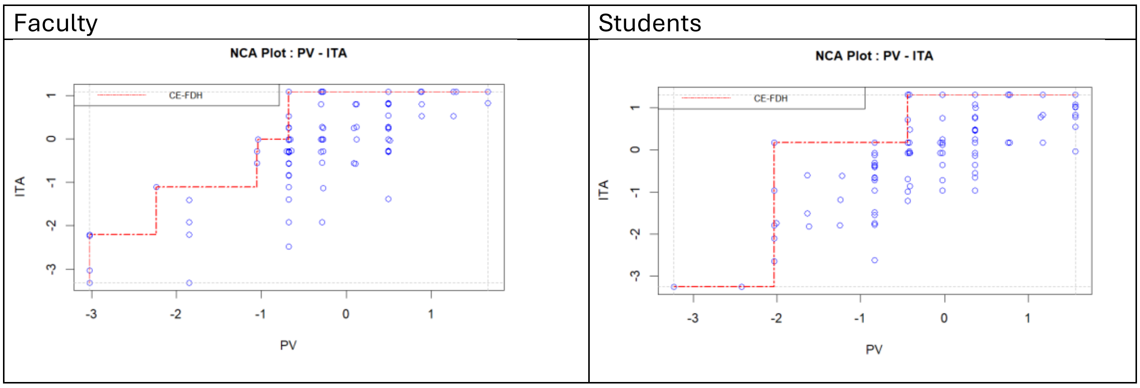
To determine whether the structural relationships differ significantly between the groups of students and faculty, we conduct a multi-group analysis (MGA), estimating the model separately for each group, and test for differences in path coefficients *(Table 4*). Despite significant differences in the level of perceived institutional resilience across groups, none of the path coefficients differ significantly between students and faculty. The group-specific estimates closely mirror the relationships observed in the full-sample model, thereby confirming the underlying structural mechanism.

The explanatory power of the model increases slightly for the student sample (R^2=0.741), while it remains relatively unchanged for the faculty sample (R^2=0.618). For both groups, the full mediation effect of AI value perception remains stable in both magnitude and significance compared to the full sample.

As a robustness check, we re-estimated the full model and the MGA, including item PV1. While the full sample estimates remain unchanged, for the MGA path coefficients for the RES→ITA path are marginally smaller in magnitude for students and marginally larger in magnitude for faculty; however, the path as well as the difference between groups remains statistically insignificant, and we observe a slight reduction in effect sizes.

However, given this robust common mechanism regarding the role of perceived institutional resilience in AI adoption—which, for both groups, is fully mediated through the perceived value of the technology—it remains puzzling how to explain observed differences in distributional patterns at particular levels of resilience and perceived value. These patterns may suggest distinct constraints across groups that cannot be captured by the PLS-SEM model alone. To explore whether specific levels of resilience or value perception are necessary to achieve AI adoption intention, we conduct a Necessary Condition Analysis using the latent variable scores (Richter *et al.*, 2020; 2022; 2023).

Regarding AI adoption intention, the effect size for the perceived value of the technology is relevant (d>0.1) for both groups, with the effect size being slightly larger for students than for faculty ($d_{Students}=0.33 > d_{Faculty}=0.27 > 0.1$) and significant (p-value < 0.001 for both). There is no relevant NCA effect size for perceived resilience on adoption intention ($0.1>d_{Students}=0.05>d_{Faculty}=0.00$), or for perceived resilience on perceived value ($0.1>d_{Student}=0.06 >d_{Faculty}=0.04$). *Figure 2* presents for each group the relevant NCA charts with the CE-FDH ceiling line for each group. The corresponding bottleneck table for PV→ ITA is presented in the *Appendix* (*Table A2*). Interestingly, regarding the relationship between perceived value and adoption intention for the student group, we observe a sharp vertical rise in the ceiling line at -2, which suggests that the perceived AI value acts as a threshold condition. Below the identified minimum level of perceived value, high adoption intention is not achievable. For the faculty group, by contrast, we observe a stair-step pattern, indicating an incremental necessary condition; that is, perceived AI value becomes step-wise more constraining as adoption intention increases, rather than reflecting a threshold effect for AI adoption in their workplace.



Source: own elaboration.

Figure 2. **NCA Charts: Student-Faculty Differences in the Role of AI Value**

With respect to resilience levels, it is important to note that the NCA is sensitive to isolated observations: if only a few respondents were removed from the analysis, a threshold would become visually detectable; however, such a pattern is not robust in the data under analysis. Accordingly, perceived institutional resilience does not function as a necessary constraint on AI adoption intention or on value perception for either group. Instead, resilience contributes indirectly (mediated by perceived value), providing a favorable context, while perceived value itself constitutes the necessary condition for adoption intention.

The bottleneck table shows that for faculty, perceived AI value is not constraining at low to moderate levels of adoption intention, but becomes binding as adoption intention increases, particularly at higher levels (e.g., around 90%), where relatively high levels of perceived value are required. This suggests that higher levels of adoption intention require correspondingly higher levels of perceived value, rather than depending on a single minimum threshold.

For students, from 10% to 70% of adoption intention, the required level of perceived value remains low and relatively constant, suggesting a threshold pattern. However, reaching higher levels of adoption intention (above 70%) requires higher levels of perceived value.

Consequently, perceived AI value emerges as the key mediating mechanism through which institutional resilience influences AI adoption intention in both groups. Among students, perceived value operates primarily as a threshold condition: once a minimum level is reached, high adoption intention becomes feasible. Among faculty, by contrast, perceived value functions as a continuous constraint, such that higher levels of adoption intention require progressively higher levels of perceived value.

4.2 Study 2: Assessing the Influence of Program Delivery Modes on AI Adoption

Considering the different delivery modes, which by nature vary in the exposure of students and faculty to digital technology, the descriptive analysis suggests some differences. In-person and online education programs exhibit a similar pattern, with a stable median value of AI adoption intention at low to moderate levels of resilience, followed by a marked increase as perceived resilience reaches high levels (*Appendix, Figure A3*). When differentiating program types by stakeholder group, the positive relationship between institutional resilience and AI adoption intention is even more pronounced among students in online or distance education programs.

In the structural model analysis, we differentiate between In-Person programs, Online or Distance programs, and Hybrid programs, examining the effect of program type on AI adoption intention. *Table 5* presents the estimates.

Table 5: Estimated path coefficients with Mode of Delivery (Full sample)

Full sample	Path coefficient	T Stat	CI
PV → ITA	0.829	30.549	[0.770; 0.878]
RES → ITA	-0.024	-0.583	[-0.107; 0.055]
RES → PV	0.328	4.754	[0.183; 0.453]
In-Person → ITA	0.124	2.610	[0.030; 0.225]
Online or Distance → ITA	0.112	2.421	[0.020; 0.208]
In-Person → RES	-0.150	-2.281	[-0.289; -0.021]
Online or Distance → RES	0.063	0.917	[-0.076; 0.186]
R^2	0.687		

Source: own elaboration.

The results suggest that both In-Person and Online or Distance program formats have a positive and statistically significant effect on AI adoption intention (H_{3a}). Relative to Hybrid programs (the reference category), students enrolled in In-Person programs and faculty working in In-Person settings report a slightly higher inclination to adopt AI. This indicates that the mode of delivery constitutes a relevant contextual factor shaping adoption behavior. However, the results for perceived institutional resilience (H_{3b}) reveal an important distinction across delivery modes. In-Person programs show a negative and statistically significant effect on perceived resilience, suggesting that stakeholders in traditional face-to-face settings perceive their institutions as less resilient than those in Hybrid programs. In contrast, there is no significant difference in perceived resilience between participants in Online or Distance programs and those in Hybrid programs.

Taken together, these findings point to a differentiated pattern in the role of delivery modes. While both In-Person and Online or Distance formats are associated with higher AI adoption intention, only In-Person programs are linked to lower perceived institutional resilience. Although the simultaneous finding of lower perceived resilience and higher adoption intention in in-person settings may appear counterintuitive, we do not observe evidence that contradicts this pattern in the data, and we revisit this finding in the discussion in light of contextual differences across delivery modes.

Table 6. Summary of results

Hypothesis	Supported/Not supported
AI Value Perception , AI Adoption Intention	
H1a: Students and faculty differ in their overall assessment of AI's value.	Not supported
H1b: Students and faculty differ in their intention to adopt AI.	Not supported
H1c: Stakeholders' overall value assessment positively influences their intention to adopt AI.	Supported
The Role of Perceived Institutional Resilience	
H2a: Students and faculty differ in their perceived institutional resilience.	Supported
H2b: Perceived institutional resilience has a positive effect on AI adoption intention, mediated by stakeholders' value perception of AI technology.	Supported
H2c: Perceived institutional resilience has a direct positive effect on AI adoption intention.	Not supported
Mode of Delivery (In-person, hybrid, online or distance)	
H3a: The mode of delivery affects AI adoption intention.	Supported
H3b: The mode of delivery affects perceived institutional resilience.	Supported

Source: own elaboration.

Summing up the inter-group differences and differences by mode of delivery in AI adoption intention, *Table 6* provides all hypotheses and results.

Discussion and Conclusion

This study advances the growing body of research on AI in higher education by emphasizing the crucial role of perceived institutional resilience in shaping stakeholder adoption behavior. Our findings offer nuanced insights into how resilience operates as an indirect influence on AI adoption intention through stakeholders' perceived value of AI. Consistent with established frameworks (especially VAM models (Kim *et al.*, 2007)), our results reaffirm that the users' overall value assessment of AI is a strong antecedent of AI adoption intention among stakeholders. That is, our model confirms that users' individual perceived value of the technology is a significant predictor of adoption intention for both students and faculty. However, by analyzing the role of perceived institutional resilience as a key factor in value-driven technology adoption, our study extends these behavioral models. While existing models (e.g., Chatterjee, Bhattacharjee, 2020) mainly focus on individual attitudes and skills, our findings demonstrate that institutional-level factors significantly shape individuals' adoption behaviors. Specifically, institutional resilience influences perceived value and, consequently, adoption intention—mirroring organizational readiness frameworks (Duchek, 2020; Teece *et al.*, 1997; Zhang *et al.*, 2021). Our structural model shows that institutional resilience impacts AI adoption indirectly through perceived value, confirming its mediating role. This aligns with research emphasizing the influence of organizational adaptability and resilience on innovation adoption (Schintler, McNeely, 2022; Zhang *et al.*, 2021).

Although students and faculty differ in their average levels of perceived resilience, contrary to our expectations, the results show no significant differences in mean levels of AI value perception or adoption between the two stakeholder groups. Instead, while their average levels of adoption are similar and follow a common underlying mechanism (where value perception mediates the effect of resilience on adoption) their behavioral paths differ. For students, once a certain value threshold is perceived, high adoption intention becomes feasible, whereas for faculty, adoption follows a stepwise pattern in which higher levels of adoption intention are associated with progressively higher levels of perceived technology value. A possible explanation lies in the contextual appreciation of value (in line with Sheth *et al.*, 1991), whereby faculty assess value primarily in terms of its contribution to their professional and organizational context, while students evaluate value in relation to their personal learning journey. That is, differences reflect variation in responses along a shared mechanism rather than fundamentally different adoption processes, suggesting the need for stakeholder-sensitive communication and support measures. These differences in resilience-level impact may also be related to structural concerns among faculty—such as pedagogical integrity and ethical issues (Selwyn, 2019)—in contrast to students' focus on AI's utility and academic convenience (Chan, Tsi, 2023; Pisica *et al.*, 2024).

These findings reinforce literature on generational and role-based differences in AI acceptance (Chan, Tsi, 2023). Therefore, institutions should develop context-sensitive strategies to support AI adoption—emphasizing ethical safeguards and pedagogical integration for faculty, and functionality and flexibility for students. The mode of program delivery further influences the relationship between resilience and AI adoption. Stakeholders in online and in-person programs exhibit higher AI adoption intentions than those in hybrid formats. This contradicts the assumption that hybrid learning naturally promotes technology integration (Pedró *et al.*, 2019). Online learners, experienced with digital platforms and tools, tend to be more receptive to AI (Kumar *et al.*, 2024). In-person learners may benefit from real-time instructional support when institutional resilience is high enough, which fosters confidence in AI applications. Conversely, hybrid learners often encounter fragmented learning experiences, which can reduce their perception of AI's relevance or coherence in the educational setting. With respect to the effect of delivery mode on resilience, this result is at first somewhat puzzling, as In-Person programs suggest higher AI adoption but show lower perceived resilience. While pure in-person settings might feel less resilient due to the lack of omnipresent digital infrastructure, other contextual factors—such as the desire for productivity or encouragement from others—may override the lack of perceived resilience to drive adoption. Thus, program modality not only affects digital exposure but also interacts with institutional perception and support to influence AI adoption. Institutions should invest in modality-specific strategies to facilitate adoption, especially in hybrid contexts where clearer AI integration is necessary.

This study demonstrates that perceived institutional resilience plays an indirect role—through AI value perception—in shaping adoption intentions. Stakeholder differences and program formats do not alter this relationship but mark important contextual distinctions. Stakeholder type influences the extent to which perceived AI value functions as a constraint on adoption intention, while the mode of delivery directly shapes adoption intention, depending on the specific user context. These findings synthesize behavioral theories with organizational resilience perspectives to provide a comprehensive understanding of AI adoption in higher education.

Practical implications

The main practical takeaways for higher education institutions seeking to foster effective and responsible AI adoption are summarized as follows.

Higher education institutions should enhance their resilience by developing dynamic capabilities, such as detecting emerging AI opportunities, seizing them through targeted pilots, and reconfiguring organizational processes to embed AI sustainably (Teece *et al*., 1997; Duchek, 2020). This involves investing in digital infrastructure, fostering cross-unit coordination, and promoting leadership adaptability, all of which boost stakeholder confidence in AI initiatives. Institutions must also establish strong AI governance frameworks that include ethical guidelines, data transparency protocols, and regular system audits to address faculty concerns about integrity and accountability (Selwyn, 2019; Vishwakarma *et al*., 2024). Since response patterns differ across stakeholder groups within the identified value-based adoption mechanism, AI implementation strategies should be tailored: faculty need structured professional development in AI literacy and pedagogical integration (Bates *et al*., 2020) to support their stepwise adoption process, while students benefit from tools that emphasize utility, personalization, and academic support to enhance their perceived value of AI in the learning process and, in turn, adoption intention. Program modality further influences adoption, with increased adoption intention for in-person programs as well as online and distance learning, compared to hybrid programs. Therefore, in line with Kumar *et al*. (2024) and Rapanta *et al*. (2020), online programs should use AI-based analytics and tutoring, in-person programs should use AI to enhance real-time interactions in phygital settings, and hybrid programs should integrate AI coherently to avoid fragmented learning experiences. These modality-sensitive strategies help institutions foster equitable, effective, and resilient AI adoption across diverse learning environments.

- **Investing in institutional resilience:** Strengthening digital infrastructure, leadership adaptability, and transparent governance fosters trust and confidence in AI initiatives, thereby increasing stakeholders' value perception of AI technology in the higher education context.
- **Tailored strategies for stakeholder groups:** Institutions should address the distinct concerns of faculty and students, as well as differences in the behavioral logic through which perceived AI value drives adoption intention in the higher education context.
    - **For faculty**, this involves emphasizing ethical safeguards, pedagogical integration, and structured professional development opportunities and training, which add value to their professional activities.
    - **For students**, institutions should highlight utility, accessibility, and flexibility in AI-supported learning tools to ensure that a clear minimum level of perceived value is reached, thereby enabling high adoption intention to become feasible and supporting academic productivity.
- **Modality-specific approaches:** Adoption strategies should reflect differences across program formats. Online programs require robust digital infrastructure and responsive support systems, in-person programs can leverage AI to complement face-to-face learning, and hybrid programs need coherent integration to prevent fragmented learning experiences.

Together, these recommendations emphasize that AI adoption in higher education cannot rely on one-size-fits-all approaches but instead follows a clear behavioral mechanism. AI deployment strategies should consider perceived institutional resilience, which drives stakeholders' value perception, the differentiated needs and value perceptions of diverse groups, and differences across program modalities.

Study limitations

While this study provides valuable insights into how perceived institutional resilience influences AI adoption across stakeholders and program modalities, several limitations should be recognized. First, the research depends on self-reported data, which is inherently prone to social desirability bias and subjectivity (Podsakoff *et al*., 2003), and measures of behavioral intentions may not fully reflect actual behavior. Second, while the structural equation model reveals significant associations and mediating effects, longitudinal or experimental studies are needed to examine how perceptions and adoption behaviors change over time (Wang *et al*., 2024). Third, generalizability remains an issue. The sample was drawn from Spanish and Latin American higher education settings. While this provides regional insights, the findings may not be entirely applicable to institutions in North America, Asia, or Africa, where institutional frameworks and digital maturity levels differ (Anuyahong *et al*., 2023; Grimmelikhuijsen, Tangi, 2024). Lastly, the analyses combined online and distance learners due to limited sample sizes. Future research with larger samples could uncover more detailed differences between these learning modes.

Recommendations for future research

Building on the current findings, several directions for future research are suggested. First, it would be interesting to explore which factors higher educational institutions prioritize to achieve perceived resilience and consequently enhance value perception and adoption of AI solutions, navigating the AI-driven paradigm shift in higher education.

Second, in line with suggestions from prior research, longitudinal analysis should be used (e.g. Kanbach *et al*., 2024; Chatterjee, Bhattacharjee, 2020), as it allows examining how perceived resilience, the perceived value of AI in education, and AI adoption intention evolve over time. Such designs would help better understand the dynamics through which institutional behavior and public perception shape AI adoption.

Third, future studies could examine behavioral data—such as AI usage logs or interactions with learning management systems—to verify self-reported measures and enhance validity. Furthermore, in line with suggestions from related work, comparative studies across different regions and types of institutions (e.g., public vs. private universities) could reveal cultural and structural differences in resilience and the underlying mechanisms of technology adoption, given that resilience and value are embedded in institutional contexts (Duchek, 2020). For example, Pisica *et al*. (2024) examined Romanian students' attitudes toward AI implementation in higher education and identified nuanced concerns about overreliance, academic integrity, and the ethical implications of automation—highlighting the importance of understanding culturally specific perceptions of AI.

Finally, researchers should examine the role of organizational leadership, ethics, and AI governance structures in influencing adoption behavior, especially among faculty who may be more skeptical of AI (Schwaeke *et al*., 2025) and whose adoption appears to follow a stepwise, value-based pattern. Ethical concerns regarding AI are not just theoretical; as Naz and Kashif (2025) demonstrate, even managers—often viewed as strategic adopters—frequently show hesitation due to worries about predictive bias, transparency, and responsibility. This underscores the need to further examine these issues in higher education contexts. Building on this, Wang (2024) introduced a resource-based model showing how AI implementation can improve managerial decision-making efficiency and organizational innovation, which suggests that future research could link perceived institutional resilience with performance outcomes like strategic agility or innovation capacity.

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INSTITUCIJŲ ATSPARUMAS, DIRBTINIO INTELEKTO DIEGIMAS IR SUINTERESUOTŲJŲ ŠALIŲ SUVOKIMAS NERAMIOJE EKONOMINĖJE APLINKOJE

Luis Toro-Dupouy, Anett Erdmann

Santrauka. Tyrime keliamas klausimas, kodėl institucijos, kurdamos dirbtinio intelekto diegimo strategijas, turėtų atsižvelgti į suinteresuotųjų šalių suvokiamą institucinį atsparumą. Nagrinėjama, kaip institucinis atsparumas veikia dirbtinio intelekto diegimo ketinimus, siekiant užpildyti spragą tarp gebėjimais pagrįsto valdymo ir suinteresuotųjų šalių elgesio ketinimų aukštojo mokslo srityje. Pasitelkus PLS-SEM ir būtinųjų sąlygų analizę daugiagrupiame modelyje išanalizuoti skirtumai tarp dėstytojų ir studentų (1 tyrimas) ir skirtingų programų įgyvendinimo būdų (2 tyrimas). Rezultatai atskleidė, kad suvokiamo institucinio atsparumo poveikis ketinimams diegti dirbtinį intelektą yra visiškai medijuojamas suinteresuotųjų šalių suvokiamos dirbtinio intelekto vertės. Nustatyta, kad šis mechanizmas išlieka stabilus įvairiose suinteresuotųjų šalių grupėse ir nepriklauso nuo programų įgyvendinimo būdo. Nors suvokiama dirbtinio intelekto vertė yra pagrindinis diegimo ketinimus skatinantis veiksnys abiejose suinteresuotųjų šalių grupėse, jų elgesio modeliai skiriasi. Studentams pakanka pasiekti tam tikrą minimalią suvokiamos dirbtinio intelekto vertės ribą, kad susiformuotų stiprus ketinimas jį diegti, o dėstytojų ketinimai didėja nuosekliau ir laipsniškiau, augant suvokiamai dirbtinio intelekto vertei. Tad būtinos vertybėmis pagrįstos dirbtinio intelekto diegimo strategijos atsižvelgiant į institucinį kontekstą ir suinteresuotųjų šalių apribojimus.

Reikšminiai žodžiai: dirbtinis intelektas; institucijų atsparumas; dirbtinio intelekto diegimas; daugiagrupė analizė; aukštasis mokslas.

Appendix

Table A1. Variables and measurement scales

Variable	Item	Item
Programs	Programs1	In-person, Online, Hybrid, Distance (completely asynchronous)
	Programs2 (multiple options)	We currently offer hybrid courses and programs. We currently offer in-person courses and programs. We currently offer online courses and programs. We currently offer distance courses and programs (completely asynchronous).
Intention to adopt	ITA1	I think that the AI based teaching and learning system is advantageous for our institution
	ITA2	I am in favour of an AI based teaching and learning system
	ITA3	I would like to use the AI based technology to its full potential
	ITA4	Overall, I think using AI based technology will enhance our organization's productivity
Perceived value	PV1	Compared to the fee I need to pay, the use of AI technology in the university offers value for money
	PV2	Compared to the effort I need to put in, the use of AI technology in the university is beneficial to me
	PV3	Compared to the time I need to spend, the use of AI technology in the university is worthwhile to me
	PV4	Overall, the use of AI technology in the university delivers me good value
Resilience	RES1	We are able to cope with changes in the university brought on by disruptions in the business environment
	RES2	We are able to easily adapt our university operations to disruptions in the business environment
	RES3	We are able to provide a quick response to the negative effects of disruptions in the business environment
	RES4	We remain aware of changes in the university environment at all times

Source: own elaboration.

Table A2: Bottleneck table PV→ITA

	ITA level	Faculty			Students		
		ITA target	PV required	% of PV range	ITA target	PV required	% of PV range
1	10	-2.871	-3.021	~0%	-2.792	-2.032	~15–20%
2	30	-1.990	-2.240	~10–15%	-1.879	-2.032	
3	50	-1.110	-2.240	~10–15%	-0.966	-2.032	
4	70	-0.229	-1.037	~35–40%	-0.052	-2.032	
5	90	0.652	-0.677	~45–50%	0.861	-0.438	~40–45%

Source: own elaboration.

Table A3. Estimated path coefficients (MGA mode of delivery)

Full sample	β_S	T Stat	CI	β_F	T Stat	CI	$\beta_S - \beta_S$ (SE)
	In-Person			Online or/and Distance			
PV → ITA	0.822	16.242	[0.724; 0.915]	0.810	21.555	[0.729; 0.874]	0.012 (0.063)
RES → ITA	-0.008	-0.129	[-0.143; 0.096]	-0.068	-1.242	[-0.178; 0.033]	0.060 (0.083)
RES → PV	0.437	3.748	[0.196; 0.660]	0.344	4.817	[0.200; 0.476]	0.093 (0.137)
R^2	0.669			0.624			

Source: own elaboration.

AI adoption intention (ITA)	1	2	3	4	5
5	4	8	25	31	28
4	3	10	38	90	18
3	0	4	24	31	6
2	1	3	5	6	0
1	4	1	2	3	0

Perceived Institutional Resilience (RES)

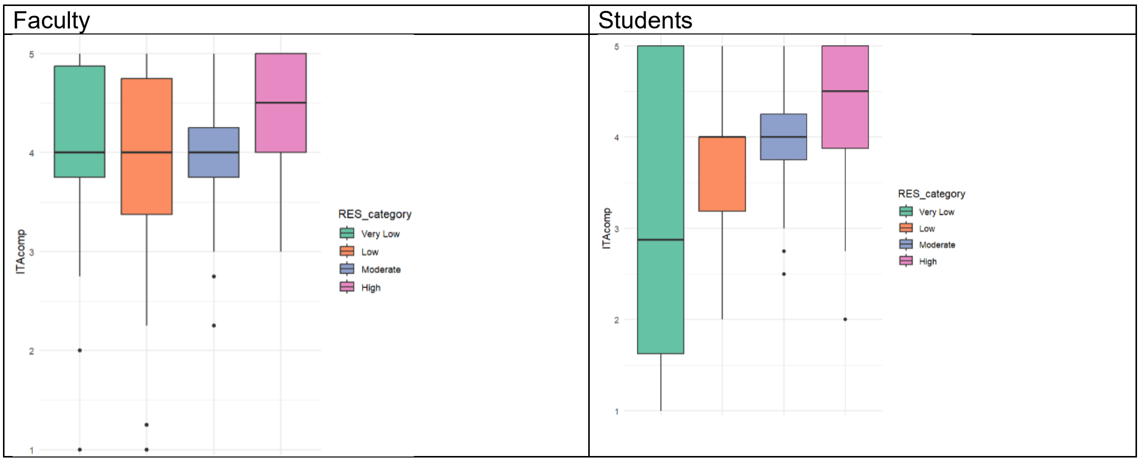
Overall Value Assessment of AI (PV)	1	2	3	4	5
5	2	4	11	15	19
4	3	6	39	82	19
3	1	11	38	54	13
2	1	5	4	8	0
1	5	0	2	2	1

Perceived Institutional Resilience (RES)

Source: own elaboration.

Figure A1. **AI Adoption Intention and Institutional Resilience: Cross-tabulation (full sample)**

The horizontal axis represents levels of institutional resilience (1–5), while the vertical axis represents levels of AI adoption intention (1–5). The values in the table indicate the absolute frequencies in the full sample, based on the items ITA1 and PV2 as examples (similar results are obtained for the remaining items).

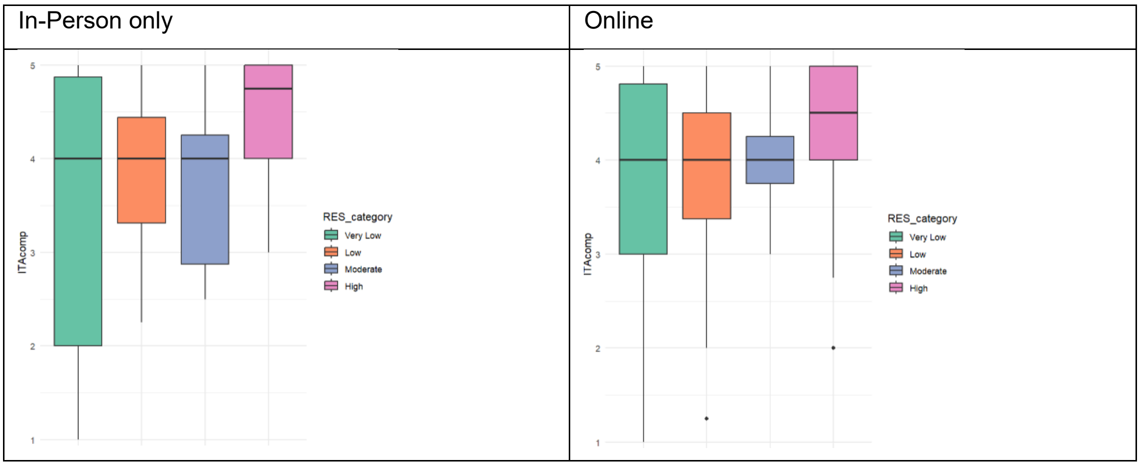


Source: own elaboration.

Figure A2. **Faculty-Students differences in AI Adoption by Level of Institutional Resilience**

To enhance representation and reliability, we use the composite mean value for each construct.[1] Composite scores were calculated as the mean of the items for each construct. We applied a rule-based grouping approach, as it aligns directly with the ordinal and bounded nature of the Likert scale (1–5) and facilitates interpretation. Accordingly, resilience levels were categorized as follows: *very low* (1–2), *low* (3), *moderate* (4), and *high* (5). For robustness, we also verified the results using a quantile-based classification, which produced consistent patterns with the rule-based approach.

[1] The sample comprises 30 institutions from 7 Spanish-speaking countries (Spain, Venezuela, Colombia, Bolivia, Peru, Andorra, Puerto Rico) with the largest share in Spain from two leading higher education institutions, one with 100% online programs and the other with 100% in-person classes. The sample was obtained through convenience sampling, as the institutions were primarily included based on accessibility and availability to participate (e.g., existing contacts and responses to invitations).



Source: own elaboration.

Figure A3. **Program-Type Differences in AI Ddoption by Level of Institutional Resilience**