Can Universities Forge Organizational Readiness for AI Adoption? Evidence from Meta-analysis

Olga Tunkevichus and Konstantin Bagrationi
Graduate School of Business, HSE University, Frankfurt am Main, Germany

oagordienko@hse.ru
kbagrationi@hse.ru

Abstract: Nowadays, universities eagerly aim for artificial intelligence (AI), yet empirical evidence remains fragmented across different levels of analysis, AI system types, and implementation contexts, blurring cumulative conclusions. Empirical models remain limited, lacking big picture that could give complex understanding of how implementation processes really work out in modern universities. This study aims to identify determinants of organizational readiness for AI adoption in higher education via meta-analysis and consolidate existing predictors into semantic blocks. A systematic search of literature yielded 28 empirical HE studies using PLS-SEM. Following PRISMA, predictors were coded into three levels and random-effects meta-analysis was conducted in R; pooled effects with confidence intervals were estimated and heterogeneity assessed using Q, I^2, and τ^2. Twelve out of fourteen observed predictors showed statistically significant positive effects on AI adoption. The strongest effect is shown by individual determinants, which confirms the behavioural logic of technology adoption models in which intention (ES = 0.907; $p < 0.001$) is the closest proximal predictor of the actual introduction of AI in HE. Cognitive predictors such as perceived usefulness and perceived ease of use also show comparable sustained effects, which confirms the importance of evaluating individual, cognitive-behavioural characteristics of personnel when implementing AI in HE processes The importance of capability-oriented factors was highlighted with AI literacy and self-efficacy, showing the importance of professional development programs for teachers to adopt AI successfully. Institutional determinants, such as social influence and competitive pressure have also shown significant results, indicating the importance of the external regulatory environment for universities. Organizational determinants also provided significant results. High heterogeneity for organizational readiness (I^2 = 0.84) indicated variation by context, AI solution type, and operationalization, supporting readiness as a dynamic capability. Given conceptual fragmentation and inconsistent modelling roles, future studies should standardize readiness measurement and test contingent and mediating mechanisms in HE AI implementation.

Keywords: AI adoption, Artificial intelligence, Higher education, Organizational readiness

1. Introduction

Artificial intelligence (AI) has rapidly moved from being a peripheral technological innovation to becoming a strategic issue for higher education institutions worldwide (Gordienko & Bagrationi, 2024). Universities are increasingly expected not only to experiment with AI tools, but also to integrate them into teaching, learning, research, administration, student support, and decision-making processes (Shwedeh, 2024). This shift is driven by several concurrent pressures: the digital transformation of educational systems, growing societal expectations for innovation, competition for students and resources, and the emergence of generative AI applications that have made AI visible and accessible to academic communities on an unprecedented scale (Michel-Villarreal et al., 2023; Wang et al., 2021). As a result, AI adoption in higher education has become a multidimensional organizational challenge that requires universities to align technological opportunities with human capabilities, institutional routines, and strategic priorities (George & Wooden, 2023).

At the same time, despite the rapidly expanding literature on AI in higher education, cumulative empirical understanding remains limited. Existing studies differ substantially in what they treat as the focal outcome, the level of analysis they prioritize, and the conceptual role assigned to readiness-related constructs (Acosta-Enriquez et al., 2024; Michel-Villarreal et al., 2023). Some studies focus on individual acceptance of AI by faculty members or students, emphasizing cognitive predictors such as perceived usefulness and perceived ease of use in line with the logic of technology acceptance models (Davis, 1989; Venkatesh et al., 2003). Other studies examine organizational conditions, such as managerial support, resource availability, IT infrastructure, or strategic alignment, while still others highlight institutional pressures, including social norms, professional expectations, or competitive dynamics (Shata & Hartley, 2025). Therefore, the field has developed as a fragmented set of parallel explanations rather than as an integrated body of evidence capable of explaining how AI adoption unfolds in universities as complex organizations.

This gap is further reinforced by conceptual ambiguity. In prior studies, readiness is operationalized inconsistently: some authors define it as a shared psychological state or perception of readiness for change, whereas others conceptualize it as a broader organizational capability, a resource-based condition, or a multidimensional construct that combines structural, cognitive, cultural, and strategic elements (Lokuge et al., 2019; Weiner, 2020). In AI-related research, this inconsistency becomes even more visible, as readiness is used in different ways across empirical models and sectors, often without a stable measurement logic or common conceptual boundary (Hradecky et al., 2022; Muhyi et al., 2025). In some models, readiness appears as a direct predictor of AI adoption; in others, it functions more as a background enabling condition that shapes the feasibility of implementation; and in still others, it is implicitly treated as an intervening mechanism linking environmental pressures, organizational arrangements, and implementation outcomes (Hradecky et al., 2022; Lokuge et al., 2019). Such inconsistency complicates cumulative comparison across studies and makes it difficult to determine whether readiness should be interpreted as a relatively stable organizational attribute, a dynamic capability, or a context-dependent configuration of preconditions for change (Lokuge et al., 2019; Weiner, 2020). Consequently, although readiness is intuitively central to AI-related transformation in universities and other organizations, its empirical status remains insufficiently theorized and weakly synthesized in the literature (Acosta-Enriquez et al., 2024; Hradecky et al., 2022).

This article addresses that problem by asking whether universities can forge organizational readiness for AI adoption and, more broadly, which determinants of AI adoption in higher education are supported by cumulative empirical evidence. The formulation “forge organizational readiness” is important here. It implies that readiness should not be treated as a naturally given state or as a static checklist of available resources. Rather, it may be understood as something that universities actively develop through managerial action, capability training, technological alignment, and responses to external pressures. This view is especially relevant for higher education institutions, where innovation often depends on gradual coalition-building, professional legitimacy, and the coordination of decentralized actors.

2. Methodology

The collection and synthesis of empirical data for meta-analysis in this study was organized in such a way as to ensure maximum completeness of coverage of relevant literature and at the same time maintain methodological comparability of the included studies. The selection of publications was carried out sequentially and included several stages, reflected in the research design (see Figure 1).

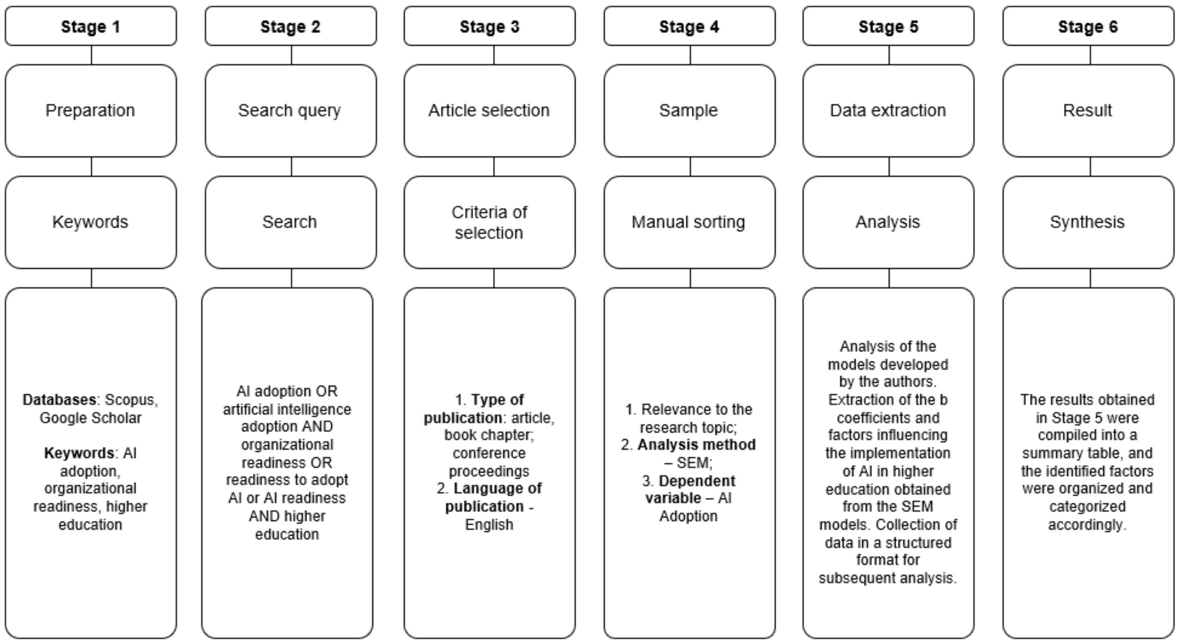

Figure 1: Meta-analysis guideline

The meta-analysis procedure was organized in accordance with PRISMA principles, focused on transparency and reproducibility of systematic reviews and meta-analytical generalizations. In dissertation logic, this means that the stages of search, exclusion, deduplication, selection by inclusion criteria, and final inclusion of research were recorded as consistent and verifiable procedures, rather than as an "expert selection" of sources (Moher et al., 2009). The search for publications was carried out in the international scientific databases Scopus, Web of Science, Google Scholar and Dimensions, which minimized the risk of incomplete coverage due to differences in the indexing of journals and thematic collections. Searching in various databases is advisable in research on digital transformation and the introduction of AI, since relevant empirical works are often distributed across different disciplinary domains (information systems, management, organizational psychology, education) and can be presented in different types of publications. Consequently, the use of multiple databases increases the likelihood of identifying full-fledged empirical results and reduces the risk of systematic exclusion of significant works (Ewald et al., 2022).

The criteria for inclusion in the meta-analysis were set based on the task of ensuring methodological uniformity of the quantitative effects to be aggregated. At this stage, an advanced search was used using combinations of keywords reflecting three semantic cores: (1) AI and AI tools, (2) readiness to change, organizational readiness and technology adoption, and (3) the context of higher education organizations.

The set of predictors included in the meta-analysis was structured according to the multilevel logic of the theories of technology adoption and organizational change and reflected three classes of factors of different nature. First, the individual characteristics of the staff were highlighted, reflecting the cognitive-evaluative and competence-based basis of AI adoption: the expected usefulness of AI, the expected ease of use of AI, AI literacy and self-efficacy. These variables correspond to a stable tradition of behavioural models, where the assessment of usefulness and ease/effort acts as proximal predictors of the intention and use of technology, and competence resources enhance the ability to learn new tools and reduce subjective barriers to acceptance. Secondly, organizational conditions reflecting the resource and management security of the implementation were assigned to a separate block: resources, management support, organizational readiness for the implementation of AI and IT consistency.

Meta-analytical processing was performed in the R environment using the metafor package and in MS Excel for auxiliary calculations and verification of intermediate results. The choice of the statistical aggregation model was made in favor of the random-effects model, which methodologically corresponds to the nature of the field under study.

Inter-study variability was assessed using the Q, I2, and t2 statistics, which are generally accepted indicators of heterogeneity in modern meta-analysis methodology. The Q statistic is used to test the null hypothesis of homogeneity of effects, that is, that the observed variability can only be explained by sampling error. The I2 index is interpreted as the proportion of the total variability of the observed effects, due not to random error, but to real heterogeneity between studies. Thus, it allows us to assess how well the results of individual works are consistent or, on the contrary, differ significantly. Finally, t2 reflects an estimate of the variance of true effects between studies and is used as a parameter in the random effects model; its value is important for understanding the scale of the intercontext variability of the predictor's influence. The use of this set of metrics complies with methodological standards for assessing heterogeneity and provides a correct basis for interpreting the sustainability of results for each factor (Higgins & Thompson, 2002)

3. Results

Table 1: Consolidated results for meta-analysis

Variavle	n	sample	ES	SE	p-value	z-value	LCI	UCI	Q total	I^2	tau^2	Decision
Behavioral intention to adopt AI	3	1186	0.907	0.104	0.000	8.744	0.703	1.11	0.805	0	0	Supported
Compatibility	2	1012	0.223	0.116	0.055	1.915	-0.005	0.451	11.546	0.913	0.025	Not supported
Complexity	2	1319	0.04	0.117	0.734	0.34	-0.189	0.268	73.778	0.977	0.04	Not supported
Effort expectancy	2	633	0.148	0.032	0.000	4.625	0.085	0.211	0.88	0	0	Supported
AI Literacy	2	674	0.319	0.088	0.000	3.615	0.146	0.493	8.893	0.888	0.014	Supported
Competitive pressure	2	1012	0.101	0.012	0.000	8.227	0.077	0.125	0.78	0	0	Supported
Organizational readiness	3	967	0.172	0.044	0.000	3.896	0.086	0.259	12.772	0.84	0.004	Supported
Perceived ease of use	6	1968	0.221	0.061	0.000	3.607	0.101	0.34	102.672	0.914	0.016	Supported
Perceived usefullness	6	1866	0.226	0.055	0.000	4.118	0.119	0.334	28.952	0.785	0.012	Supported
Resources	2	1012	0.123	0.02	0.000	6.114	0.084	0.163	0.026	0	0	Supported
AI strategic alignment	2	1012	0.106	0.026	0.000	4.115	0.056	0.157	0.128	0	0	Supported
Self-efficacy	2	598	0.319	0.088	0.000	3.615	0.146	0.493	8.893	0.888	0.014	Supported
Social influence	3	620	0.308	0.11	0.005	2.793	0.092	0.525	13.863	0.928	0.023	Supported
Management support	3	1412	0.204	0.06	0.001	3.406	0.087	0.322	14.272	0.89	0.01	Supported

The results of meta-analysis are presented in table 1. Most of the identified factors demonstrate statistically significant positive effects on the introduction of AI technologies (12 out of 14). The strongest effect is shown by *individual determinants*, which confirms the behavioral logic of technology adoption models in which intention (ES = 0.907; p <0.001) is the closest proximal predictor of the actual introduction of AI in HE. Cognitive predictors such as perceived usefulness (ES = 0.226; p <0.001) and perceived ease of use (ES = 0.221; p <0.001) also show comparable sustained effects, which confirms the importance of evaluating individual, cognitive-behavioral characteristics of personnel when implementing AI in HE processes. Along with them, an essential role is played by AI literacy (ES = 0.319; p <0.001) and self-efficacy (ES = 0.319; p <0.01), which reflect the readiness of employees not only to understand the principles of functioning of AI systems, but also to confidently integrate them into professional activities. *Institutional determinants* such as social influence (ES = 0.308; p <0.001) and competitive pressure (ES = 0.101; p <0.001) indicate the importance of the external regulatory environment and the market context. *Organizational determinants* are also significant: management support (ES = 0.204; p <0.01), organizational readiness (ES = 0.172; p <0.001), resources (ES = 0.123; p <0.001) and AI strategic alignment (ES = 0.106; p <0.001). Collectively, these results indicate that the introduction of AI into HE processes is not so much of a technological, rather than an organizational process, which is determined by the maturity of management processes, the ability to make organizational changes, and the consistency of AI with the existing architecture of goals and solutions.

4. Discussion

The results of this meta-analysis show that AI adoption in higher education should be interpreted as a multilevel process shaped by individual, organizational, and institutional determinants rather than as a purely technological or user-level phenomenon (Tunkevichus, O., & Bagrationi, 2025). This finding is important because prior research on AI in higher education has often emphasized isolated predictors, specific AI tools, or single implementation settings, thereby limiting cumulative understanding of how adoption unfolds across universities as complex organizations (Michel-Villarreal et al., 2023). In this regard, the present study contributes to literature by empirically consolidating fragmented evidence and showing that the implementation of AI in universities depends on the joint action of cognitive, organizational, and environmental mechanisms rather than on one dominant explanatory block.

More specifically, the meta-analytic results support the idea that universities adopt AI not simply because technologies become available, but because relevant actors perceive them as useful, manageable, legitimate, and organizationally supportable (Davis, 1989; Venkatesh et al., 2003; Paul, 2020). Such a pattern is especially important in higher education, where implementation processes are embedded in professional autonomy, institutional regulation, and organizational complexity rather than in purely hierarchical decision-making structures (Wang et al., 2021; Michel-Villarreal et al., 2023). Accordingly, the findings suggest that AI adoption in higher education should be conceptualized not as a single act of acceptance, but as a layered process in which individual readiness, organizational support, and external pressure jointly shape the transition from intention to actual implementation (Venkatesh et al., 2003; Paul, 2020).

The strongest beta effect was observed for behavioral intention, which is fully consistent with the core proposition of behavioral technology adoption models that intention is the closest proximal predictor of actual use or implementation behavior (Venkatesh et al., 2003). This result indicates that even in the context of universities as creative organizations, where AI initiatives may be supported through infrastructure, pilot programs, or formal strategies, actual adoption still depends heavily on whether individuals form a concrete readiness to use AI in their professional practice. In other words, organizational initiatives do not automatically translate into implementation unless they are mediated by individual motivational commitment to adoption.

The significant effects of perceived usefulness and perceived ease of use further confirm that the explanatory logic of TAM and UTAUT remain highly relevant for AI adoption in higher education (Davis, 1989; Venkatesh et al., 2003). These results suggest that university staff are more likely to support and use AI when they believe that such tools can improve work outcomes and when the technology is not perceived as excessively difficult to understand or operate (Davis, 1989; Venkatesh et al., 2003; Wang et al., 2021). This is particularly important for universities because academic and administrative employees typically operate under high workload, fragmented time resources, and professional accountability, which makes the subjective balance between expected benefit and required effort especially salient (Wang et al., 2021; Michel-Villarreal et al., 2023). Therefore, the findings confirm that AI adoption in higher education still follows the rational-evaluative logic of technology acceptance, even though it unfolds in a more institutionally dense environment than many traditional IT contexts.

The significant positive effects of AI literacy and self-efficacy deepen this interpretation by showing that adoption depends not only on utility beliefs, but also on users' confidence and competence in working with AI-related tools which go in alignment with basic principles presented by Compeau & Higgins in 1995. This result is theoretically meaningful because it extends the classic utility-centered tradition of technology acceptance toward a more capability-based understanding of readiness (Venkatesh et al., 2003). In the context of higher education, this means that even when AI is perceived as useful, adoption may remain limited if employees do not feel capable of interpreting outputs, managing risks, or integrating AI into discipline-specific tasks (Wang et al., 2021; Michel-Villarreal et al., 2023). Thus, the meta-analysis supports the argument that universities need not to only build positive attitudes toward AI, but also to develop a competence base among staff to enable meaningful adoption (Paul, 2020).

A second important result is that organizational variables also demonstrate significant positive effects, including management support, resources, organizational readiness, and AI strategic alignment. This pattern shows that AI adoption in universities cannot be fully explained by user perceptions alone and must also be treated as an organizational implementation process requiring coordination, legitimization, and infrastructural support (Liang et al., 2007; Paul, 2020). The significance of management support is especially consistent with prior research showing that leadership involvement helps legitimize technological change, reduce uncertainty, allocate resources, and remove barriers to implementation (Liang et al., 2007). In the case of AI, where concerns about ethics, data quality, responsibility, and changing work practices are particularly pronounced, visible managerial support may be even more important than in conventional IT adoption contexts (Michel-Villarreal et al., 2023).

The positive role of resources likewise confirms that the feasibility of AI adoption depends on the availability of financial, technical, temporal, and human capacities within the organization rather than on attitudes alone. In higher education, this includes not only access to digital tools and infrastructure, but also the institutional capacity to support training, experimentation, technical integration, and governance procedures around data and AI use (Wang et al., 2021; Michel-Villarreal et al., 2023). The significance of AI strategic alignment further suggests that implementation becomes more likely when AI initiatives are perceived as compatible with existing organizational systems, priorities, and digital architecture rather than as isolated or symbolic experiments (Henderson & Venkatraman, 1993). Together, these findings indicate that universities need organizational coherence around AI, not merely local enthusiasm for individual tools (Paul, 2020).

Most importantly, organizational readiness itself showed a statistically significant positive effect, which confirms that readiness is not merely a rhetorical or background notion, but an empirically meaningful determinant of AI adoption in higher education (Paul, 2020). At the same time, the very high heterogeneity observed for organizational readiness suggests that this construct does not operate in a stable or uniform way across studies. This likely reflects substantial variation in how readiness is conceptualized and measured, with some studies treating it as a broad organizational capability, others as a resource-related condition, and still others as a managerial or psychological preparedness factor (Paul, 2020; Tunkevichus & Bagrationi, 2025). Therefore, the present findings support the interpretation of organizational readiness as a dynamic and context-sensitive capability rather than a single fixed organizational attribute (Paul, 2020).

The significance of social influence and competitive pressure shows that AI adoption in higher education is also shaped by institutional and environmental mechanisms, not only by internal organizational factors (Horani et al., 2023). Social influence captures the normative dimension of adoption: individuals are more likely to support or use AI when meaningful others, such as colleagues, leaders, or professional communities, consider such behavior appropriate or expected (Venkatesh et al., 2003). In universities, this mechanism is particularly plausible because academic work is embedded in professional norms, reputational expectations, and community-based judgments regarding legitimacy, quality, and acceptable practice (Bouter, 2024). Therefore, the meta-analytic significance of social influence indicates that AI adoption in higher education is not purely instrumental, but also socially mediated.

The significance of competitive pressure further supports the relevance of the external environment in shaping institutional responses to AI (Erdmann & Toro-Dupouy, 2025). Universities increasingly operate in competitive fields defined by rankings, student recruitment, research visibility, funding opportunities, and broader narratives of digital modernization (Wang et al., 2021; Michel-Villarreal et al., 2023). Under such conditions, AI may be adopted not only because it improves internal efficiency, but also because it signals innovativeness, relevance, and strategic responsiveness to change (Sánchez-Rodríguez et al., 2025). Thus, the results indicate that AI adoption in higher education should also be interpreted as a response to institutionalized expectations and competitive pressures in the broader environment (Tunkevichus & Bagrationi., 2025).

5. Conclusion

This study sets out to identify the determinants of AI adoption in higher education and to clarify the role of organizational readiness through a meta-analysis of empirical PLS-SEM studies. The results show that AI adoption in universities is shaped by a broad set of statistically significant determinants spanning individual, organizational, and institutional levels. The strongest effect was observed for behavioral intention, which confirms the continuing relevance of behavioral technology adoption models in explaining actual implementation outcomes (Ajzen, 1991; Venkatesh et al., 2003). At the same time, significant effects for perceived usefulness, perceived ease of use, AI literacy, self-efficacy, management support, resources, strategic alignment, social influence, competitive pressure, and organizational readiness demonstrate that AI adoption in higher education cannot be reduced to intention alone (Agrawal, 2023).

The findings therefore support a multilevel interpretation of AI implementation in universities. AI adoption is simultaneously a behavioral process, an organizational change process, and an institutionally embedded response to environmental pressures (Venkatesh et al., 2003; Paul, 2020; Wang et al., 2021). Within this broader architecture, organizational readiness occupies an important but conceptually unstable position. Its statistically significant effect confirms that readiness matters empirically, yet its high heterogeneity indicates that the field still lacks a sufficiently standardized and consistent understanding of how readiness should be defined and measured across contexts (Higgins & Thompson, 2002; Paul, 2020; Tunkevichus & Bagrationi, 2025). For this reason, organizational readiness should be interpreted not as a fixed background state, but as a dynamic capability emerging from the interaction of cognitive, structural, managerial, and institutional conditions (Paul, 2020).

The study contributes to literature in three main ways. First, it consolidates fragmented empirical evidence on AI adoption in higher education and shows that the field is more cumulative than it appears when viewed through isolated studies alone (Wang et al., 2021). Second, it demonstrates that organizational readiness is a meaningful explanatory construct, while also revealing the extent of conceptual fragmentation surrounding it (Paul, 2020; Tunkevichus & Bagrationi, 2025). Third, it provides support for moving from a narrow "technology acceptance" lens toward a broader framework of organizational readiness for AI adoption in universities, which better captures the complexity of higher education institutions as implementation environments (Davis, 1989; Venkatesh et al., 2003; Michel-Villarreal et al., 2023).

From a practical standpoint, the results imply that universities can forge readiness for AI adoption, but only through coordinated multilevel action. Successful implementation requires not only useful and accessible technologies, but also staff capability-building, managerial support, resource allocation, alignment with institutional systems, and sensitivity to the broader normative and competitive environment (Liang et al., 2007; Michel-Villarreal et al., 2023). Therefore, universities seeking to institutionalize AI should treat readiness not as a preliminary checklist, but as an ongoing process of organizational development and strategic adaptation (Paul, 2020).

At the same time, the study points to the need for further work. Future research should develop more standardized measures of organizational readiness, examine mediated and contingent mechanisms of AI implementation, and differentiate readiness across AI types, organizational forms, and national higher education systems (Paul, 2020; Michel-Villarreal et al., 2023; Tunkevichus & Bagrationi, 2025). Such work would strengthen the analytical precision of the readiness concept and improve the cumulative explanatory power of research on AI adoption in higher education.

Ethics Declaration: This study did not involve human participants, personal data collection, or experimental interventions and therefore did not require ethical clearance

AI Declaration: During the preparation of this paper, AI tools (specifically, ChatGPT 5.2. by OpenAI) were used to assist in language editing and improving the clarity and fluency of the text. The content generated by the AI was critically reviewed, edited, and integrated by the authors to ensure accuracy, originality, and academic integrity.

References

Acosta-Enriquez, B. G., Farroñan, E. V. R., Zapata, L. I. V., Garcia, F. S. M., Rabanal-León, H. C., Angaspilco, J. E. M., & Bocanegra, J. C. S. (2024). Acceptance of artificial intelligence in university contexts: A conceptual analysis based on UTAUT2 theory. *Heliyon*, *10*(19).

Agrawal, K. (2023). Towards Adoption of Generative AI in Organizational Settings. *Journal of Computer Information Systems, 64*, 636 - 651.

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, *50*(2), 179-211.

Bouter, L. (2024). Why research integrity matters and how it can be improved. *Accountability in Research*, *31*(8), 1277-1286.

Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS quarterly*, *19*(2), 189-211.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319–340.

Erdmann, A., & Toro-Dupouy, L. (2025). The influence of the institutional environment on AI adoption in universities: identifying value drivers and necessary conditions. *European Journal of Innovation Management*, *28*(9), 4365-4398.

Ewald, H., Klerings, I., Wagner, G., Heise, T. L., Stratil, J. M., Lhachimi, S. K., ... & Nussbaumer-Streit, B. (2022). Searching two or more databases decreased the risk of missing relevant studies: a metaresearch study. *Journal of clinical epidemiology*, *149*, 154-164.

George, B., & Wooden, O. (2023). Managing the strategic transformation of higher education through artificial intelligence. *Administrative Sciences*, *13*(9), 196.

Gordienko, O., & Bagrationi, K. (2024, September). Global integration of artificial intelligence in higher education sector: a bibliometric analysis. In *European Conference on Knowledge Management,* (pp. 270-276).

Higgins, J. P. T., & Thompson, S. G. (2002). Quantifying heterogeneity in a meta-analysis. *Statistics in medicine*, *21*(11), 1539–1558.

Horani, O., Al-Adwan, A., Yaseen, H., Hmoud, H., Al-Rahmi, W., & Alkhalifah, A. (2023). The critical determinants impacting artificial intelligence adoption at the organizational level. *Information Development, 41*, 1055 - 1079.

Hradecky, D., Kennell, J., Cai, W., & Davidson, R. (2022). Organizational readiness to adopt artificial intelligence in the exhibition sector in Western Europe. *International journal of information management*, *65*, 102497.

Liang, H., Saraf, N., Hu, Q., & Xue, Y. (2007). Assimilation of Enterprise Systems: The Effect of Institutional Pressures and the Mediating Role of Top Management. *MIS quarterly*, *31*(1), 59-87.

Lokuge, S., Sedera, D., Grover, V., & Dongming, X. (2019). Organizational readiness for digital innovation: Development and empirical calibration of a construct. *Information & management*, *56*(3), 445-461.

Michel-Villarreal, R., Vilalta-Perdomo, E., Salinas-Navarro, D. E., Thierry-Aguilera, R., & Gerardou, F. S. (2023). Challenges and opportunities of generative AI for higher education as explained by ChatGPT. *Education Sciences*, *13*(9), 856.

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & PRISMA Group*, t. (2009). Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *Annals of internal medicine*, *151*(4), 264–269.

Paul, M. (2020). Organisational readiness for Artificial Intelligence adoption. *Turku School of Economics*, 1–65.

Shata, A., & Hartley, K. (2025). Artificial intelligence and communication technologies in academia: faculty perceptions and the adoption of generative AI. *International Journal of Educational Technology in Higher Education*, *22*(1), 14.

Sánchez-Rodríguez, A., García-Vidal, G., Fernández-Ochoa, Y., Martínez-Vivar, R., Gavilanes-Venegas, A. E., & Pérez-Campdesuñer, R. (2025). Navigating Uncertainty Through AI Adoption: Dynamic Capabilities, Strategic Innovation Performance, and Competitiveness in Ecuadorian SMEs. *Administrative Sciences*, *15*(12), 468.

Shwedeh, F. (2024). The integration of artificial intelligence (AI) into decision support systems within higher education institutions. *Nanotechnology Perceptions*, *20*(5), 331-357.

Tunkevichus, O., & Bagrationi, K. (2025). People and Machines or People Against Machines? How Readiness to Artificial Intelligence is Changing Higher Education: A Bibliometric Analysis. *European Conference on Innovation and Entrepreneurship*, 759–766.

Venkatraman, N., Henderson, J. C., & Oldach, S. (1993). Continuous strategic alignment: Exploiting information technology capabilities for competitive success. *European Management Journal*, *11*(2), 139-149.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425–478.

Wang, Y., Liu, C., & Tu, Y.-F. (2021). Factors affecting the adoption of AI-based applications in higher education. *Educational Technology & Society*, *24*(3), 116–129.

Weiner, B. J. (2020). A theory of organizational readiness for change. In *Handbook on implementation science* (pp. 215-232). Edward Elgar Publishing.