

Tracing The Digital Transformation: A Bibliometric Investigation Of Artificial Intelligence Adoption In Higher Education

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Article Info	ABSTRACT
Article history: Received 05 01, 2025 Revised 05 07, 2025 Accepted 05 21, 2025	This study aimed to track the digital transformation journey through the lens of AI adoption in higher education from 2010 to 2024. Using a data-based bibliometric method from Scopus, this study identified the dominant theories used in AI adoption intention studies and conceptual structures. The literature selection process was carried out systematically using the PRISMA method to ensure transparency and accuracy in document selection. Data analysis used bibliometric techniques to analyse the research landscape quantitatively and was conducted using VosViewer Software. The analysis results show that research on AI adoption intention has experienced an annual growth of 34.15%, with most publications using the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) approaches. Network visualisation revealed fragmentation in this research, where several clusters of theories develop separately without strong integration. Overlay visualisation showed a shift from technology acceptance model-based studies to exploration of ethical impacts, algorithm transparency, and AI regulation in higher education. Density visualisation confirmed that although technical factors have been widely studied, AI's social and policy aspects are still underexplored. This research provides a more comprehensive conceptual mapping and identifies research gaps that future studies can fill.
Keywords: Artificial intelligence Adoption intention Higher education Bibliometric	
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INTRODUCTION

Rapid advances in artificial intelligence (AI) technology have transformed various sectors, including higher education. AI in academic environments offers a variety of potentials, from personalising learning and automating administration to increasing the efficiency of decision-making (Zawacki-Richter et al., 2019). AI's disruptive potential in reshaping institutional practices, pedagogical models, and administrative operations is now evident throughout higher education landscapes worldwide (López-Chila et al., 2024; Youcef & fares, 2024). The core phenomenon driving the digital transformation in these institutions is the adoption of AI technologies, which offers both promising opportunities and significant challenges. This work recognises that AI enhances operational effectiveness and redefines academic roles and

governance structures in the era of rapid digital evolution (Singh & Hiran, 2022; Youcef & fares, 2024).

The urgency behind this research was underscored by the accelerated pace of technological change amid the broader context of the Fourth Industrial Revolution (Shenkoya & Kim, 2023). As higher education institutions (HEIs) face increasing demands for efficiency, personalisation, and improved learning outcomes, the integration of AI has emerged as a strategic imperative (Shi & Wan, 2024). Furthermore, the impact of digital transformation has been accentuated by the need to address inequities in access to technology, the challenges of maintaining academic integrity, and the transformation of traditional teaching methodologies (George & Wooden, 2023). This convergence of factors creates a critical impetus for academic inquiry and policy intervention, calling for comprehensive investigations into AI adoption patterns and their long-term implications.

The research problem addressed in this study revolves around the persistent fragmentation in the literature concerning AI integration in HEIs. Despite the growing interest in digital transformation and the proliferation of empirical studies in this area, there exists a lack of consensus regarding the determinants, challenges, and outcomes associated with AI adoption (López-Chila et al., 2024; Reis-Marques et al., 2021). For example, while some studies have demonstrated that AI can enhance operational efficiencies by automating administrative tasks and personalising learning experiences (López-Chila et al., 2024; Shi & Wan, 2024) others have highlighted significant obstacles, such as the need for substantial financial investments, a shortage of skilled personnel, and concerns regarding data privacy and ethical use (K. S. Chan & Zary, 2019; Zawacki-Richter et al., 2019).

In this context, the research gap is twofold. First, previous investigations have largely focused on isolated aspects of AI integration, such as its impact on teaching and learning or the operational challenges associated with its adoption (Reis-Marques et al., 2021). As a result, there has been limited effort to holistically map the academic discourse surrounding adoption processes and the emergent outcomes of AI applications in higher education (Iffath Unnisa Begum, 2024). Second, while some studies have employed bibliometric techniques to explore AI trends (Saleem et al., 2023), there remains a dearth of research that combines comprehensive bibliometric mapping with a detailed investigation of the digital transformation process in HEIs. This study aims to address these gaps, contributing to the academic discourse by providing a systematic investigation that covers the breadth and depth of AI adoption in higher education.

The novelty of this study lies in its integrative approach to bibliometric analysis, which facilitates a nuanced understanding of the global scholarly contribution to the discourse on AI adoption in HEIs. Unlike previous studies that have treated various components of technological integration in isolation (López-Chila et al., 2024), this research synthesises evidence from diverse sources to highlight the interplay between technological, pedagogical, and institutional changes. This article quantifies the research output by employing bibliometric mapping and qualitatively distinguishes the distinct trajectories and thematic clusters that define the field (Saleem et al., 2023). This dual approach ensures enriched insight into the evolving dynamics of digital transformation in higher education, making it possible to propose more targeted strategies to adopt AI effectively.

To mapping the research landscape, the study further delineated the research objectives that guide its inquiry. First, it seeks to identify and analyse the historical evolution of AI applications in higher education, shedding light on the critical milestones and pioneering studies that have shaped current practices (Saleem et al., 2023). Second, it aims to examine the

current State's of AI adoption by categorising the determinants—from institutional capacity to cultural readiness—that influence successful integration in various educational contexts (Shi & Wan, 2024). Third, it provides an evaluative framework for understanding the challenges associated with AI adoption, particularly those concerning data privacy, equitable access, and the preservation of academic integrity (Chan & Zary, 2019). Fourth, the research objectives include analysing emerging trends and identifying future directions for policymakers and institutional leaders who must navigate the complex landscape of digital innovation in higher education. Researchers and policymakers alike are seeking to foster sustainable and inclusive digital transformation within educational settings.

LITERATURE REVIEW

Factors Influencing AI Adoption Intention In Higher Education

The intention to adopt artificial intelligence (AI) in higher education is influenced by a diverse set of factors that interact at the individual, institutional, and technological levels. One of the critical determinants is the role of facilitating conditions and support structures within institutions. Research indicates that when decision-makers, respected educators, and administrators actively endorse AI initiatives, the perceived legitimacy and viability of AI applications increase, thereby driving adoption intentions (Alotaibi & Alshehri, 2023; Mohsin et al., 2024). In this regard, facilitating conditions such as robust IT infrastructure, technical support, and resource availability are pivotal in creating an environment that eases the integration of AI tools and fosters a positive attitude among teachers and learners ((Algerafi et al., 2023; Mohsin et al., 2024).

At the individual level, factors such as perceived usefulness, ease of use, and a well-matched task-technology fit (TTF) play significant roles in shaping adoption intentions. Studies highlight that the degree to which AI technologies are deemed effective in complementing existing academic tasks underpins the willingness of faculty and students to incorporate these tools into their daily practices (Abdekhoda & Dehnad, 2024; Yin & Goh, 2024). Additionally, the development of AI literacy is crucial: higher education students and educators alike need to comprehend both the capabilities and limitations of AI systems, which fuels their readiness to adopt and innovate using these technologies (Chan & Hu, 2023). Trust in AI technology, bolstered by prior exposure and positive user experiences, further augments confidence in AI systems and encourages continued use (Salifu et al., 2024).

Social influence factors manifest through peer exchanges, the sharing of positive experiences, and endorsements from influential stakeholders. The presence of early adopters and success stories circulating within professional networks can mitigate resistance and engender collective momentum toward AI integration within educational contexts (Mohsin et al., 2024; Tian et al., 2024). Nonetheless, some studies note that the impact of social influence may be less pronounced in certain scenarios, where technical and facilitating conditions overshadow the potential sway of social dynamics (Palmer et al., 2023; Tian et al., 2024). This suggests a complex interplay wherein social endorsements are important, yet they function optimally when aligned with clear evidence of AI's practical benefits.

Institutional support and leadership commitment are also essential components. The active involvement of top management and policymakers in championing AI-based initiatives contributes to a coherent strategic vision. Research into organizational-level AI adoption reveals that factors such as management support, regulatory frameworks, and competitive

pressures reinforce a conducive climate for systematic AI integration (Cabero-Almenara et al., 2024; Horani et al., 2023). In higher education, such mechanisms enhance technological alignment with academic goals and promote innovative pedagogical practices that leverage AI for improved teaching and learning outcomes (Tanantong & Wongras, 2024).

Theories In AI Adoption Intention

The adoption intention of artificial intelligence (AI) in higher education has been explored through various theoretical lenses, each contributing to our understanding of user behavior and institutional dynamics. The predominant theories include the Unified Theory of Acceptance and Use of Technology (UTAUT and its extension UTAUT2), the Technology Acceptance Model (TAM), Diffusion of Innovation (DOI), Task-Technology Fit (TTF), the Expectation-Confirmation Model (ECM), and the Theory of Planned Behavior (TPB), as well as perspectives on perceived risk.

At the forefront, the UTAUT framework has been widely applied to understand AI adoption in educational contexts. A study by Mohsin et al. (2024) highlighted that the endorsement of AI by influential stakeholders in higher education facilitates the diffusion of technology through established social networks. In alignment with this, Tanantong and Wongras (2024) demonstrated that factors such as performance expectancy and social influence are critical determinants of AI adoption, findings which have been corroborated in studies like that of that emphasize perceived benefits in AI adoption (Okela, 2024), although direct links to generative AI are less explored. These constructs are further refined in the UTAUT2 model, as Abdullah and Mohd Zaid (2023) reported that user perceptions regarding the utility and ease of use of generative AI technologies significantly drive behavioral intentions among university students, thereby reinforcing the importance of perceived benefits in technology acceptance.

Complementing the UTAUT perspective, the Technology Acceptance Model (TAM) has also been employed to explain AI adoption intention. A study by Kanont et al. (2024) utilized TAM to elucidate that perceived usefulness and ease of use are particularly influential in the context of generative AI as a learning assistant. These insights are echoed in the broader TAM literature, suggesting that when students and educators recognize tangible benefits and low complexity in implementing AI, their willingness to adopt these technologies increases markedly.

The Diffusion of Innovation (DOI) theory provides another theoretical lens by emphasizing the communication channels and social mechanisms through which AI innovation spreads within higher education. A study by Bag et al. (2024) extended DOI theory to illustrate that attributes such as relative advantage, compatibility, and observability are critical for the gradual acceptance of AI-driven innovations. In this framework, early adopters in academic communities act as change agents who help reduce uncertainties and foster broader acceptance, linking innovations to institutional culture.

While UTAUT, TAM, and DOI focus heavily on individual perceptions and social influence, Task-Technology Fit (TTF) theory adds the dimension of how well AI technologies align with academic tasks. A study by Abdekhoda and Dehnad (2024) empirically demonstrated that a good fit between AI capabilities and teaching requirements significantly boosts faculty intention to adopt AI. This alignment is essential, as it ensures that the technology meets both technical specifications and adequately supports the pedagogical processes intrinsic to higher education.

In addition, the Expectation-Confirmation Model (ECM) and the Theory of Planned Behavior (TPB) provide valuable insights into dynamic and behavioral aspects of AI adoption. Tian et al. (2024) integrated ECM with UTAUT to reveal that user satisfaction and confirmation of expectations are key drivers of continuous usage of AI chatbots among postgraduate students. Similarly, Yin and Goh (2024) used TPB to show that attitudes, subjective norms, and gender differences can shape the behavioral intention to utilize AI, providing a more granular understanding of user motivation within the academic environment.

Finally, research addressing perceived risks further nuances the adoption theories. A study by Wu et al. (2022) incorporated Perceived Risk Theory with UTAUT by examining how concerns about potential adverse effects may dampen students' willingness to accept AI-assisted learning environments. Although such risks may not always exert a strong negative influence, addressing them through enhanced technical self-efficacy and better communication about AI benefits can mitigate uncertainties and fortify adoption intentions.

METHODS

This study's methodology was designed to ensure a systematic, transparent, and reproducible approach to mapping the research landscape on AI adoption in higher education. A rigorous three-stage process was implemented to achieve the research objectives: data sourcing, data selection, and data analysis.

Data Source

The Scopus database was chosen as the primary data source to address the research objectives, owing to its recognised status as one of the largest and most authoritative academic databases. Scopus provides extensive coverage, including high-quality publications from reputable journals across a comprehensive spectrum of subject areas. Including journals, conferences, books, and book chapters indexed across Scopus Q1 to Q4 ensures that the dataset reflects both pioneering and emerging scholarship in the field. This selection was particularly strategic because it allows the study to capture current trends in publication volume, research collaboration, and conceptual evolution, thus offering high academic validity and a robust basis for bibliometric mapping. Networks and keyword clusters serve as the backbone for the subsequent bibliometric analysis.

Data Selection

The study adopted a systematic data selection process by implementing the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology (*provided in figure 1*). This stepwise approach was integral in filtering the literature transparently and methodically, thus ensuring that only the most relevant documents were included. Initially, a broad search using defined keywords was performed in Scopus, yielding many potential sources. All duplicates were removed in the early data collection stage, and the documents were screened based on predetermined inclusion and exclusion criteria (Page et al., 2021).

Specifically, the inclusion criteria for this study were set as follows: only data in the form of journal articles, conference proceedings, books, and book chapters were considered; documents must be written in English; and the publication period was restricted to the years 2010 through 2024. These criteria were selected to ensure that the analysis encompasses a comprehensive range of high-quality and peer-reviewed academic sources while also capturing the dynamic evolution of research within the specified period.

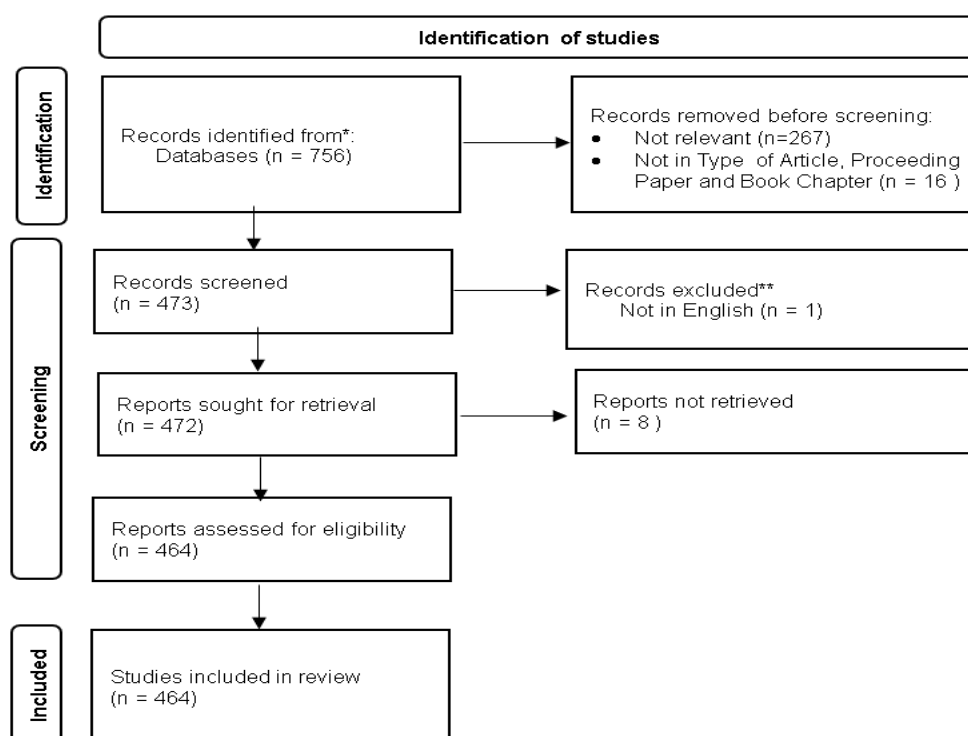


Figure 1. PRISMA flow diagram of literature screening and selection

Data Analysis

Following data selection, the study continues with data analysis using bibliometric techniques to analyse the research landscape quantitatively. Bibliometric analysis is a powerful quantitative method that allows for visualising and evaluating publication patterns, thematic evolution, and interrelationships among key concepts in the literature (Oladinrin et al., 2023).

The analysis was conducted using the VosViewer Software, a comprehensive toolkit that facilitates advanced bibliometric analysis and visualisation. VOSviewer represents a significant advancement in bibliometric analysis by enabling researchers to generate comprehensive and visually appealing network maps from complex bibliographic datasets. Its capacity to integrate various forms of bibliometric data empowers scholars to uncover hidden patterns and interrelationships within the academic literature. By offering features such as cluster mapping, overlay visualisation, and density analysis, VOSviewer facilitates the identification of key contributors and dominant topics while also aiding in understanding research domain evolution and directional shifts.

RESULTS AND DISCUSSION

Main Information

Research on the intention to adopt artificial intelligence (AI) in higher education covering the period 2010 to 2024 shows the main characteristics of the dataset used (Table 1). Overall, 464 documents are part of this analysis, with an average annual growth rate of 34.15%. This finding shows that research on this topic is growing rapidly, especially in recent years, along with the increasing adoption of AI in various aspects of higher education.

Table 1. Main Information Research Data

Description	Results	Description	Results
MAIN INFORMATION ABOUT DATA			
Timespan	2010:2024	AUTHORS	
Sources (Journals, Books, Conference Proceedings)	259	Authors	1379
Documents	464	Authors of single-authored docs	47
Annual Growth Rate %	34.15	AUTHORS COLLABORATION	
Document Average Age	1.5	Single-authored docs	51
Average citations per doc	18.73	Co-Authors per Doc	3.44
References	0	International co-authorships %	34.7
DOCUMENT CONTENTS		DOCUMENT TYPES	
Keywords Plus (ID)	1309	articles	402
Author's Keywords (DE)	1370	article article	3
		conference paper	58
		conference paper article	1

Source : Prepared by Author, 2025

In terms of document age, the average age of documents in this dataset is 1.5 years, indicating that research on AI adoption intention is still relatively new and dynamic, with many recent publications supporting the development of this study. Nevertheless, each document has an average of 18.73 citations, indicating that publications in this field have received considerable attention in the academic community. Interestingly, however, in the results of this analysis, no references were found to be used in the dataset, which may be related to limitations in metadata processing or the methodology used in bibliometric data extraction.

In terms of publications, research on AI adoption intentions has been published in 259 sources, including journals, books, and conference proceedings. These findings show that this topic has a wide scope and has received attention from various disciplines. In addition, there are 1309 keywords from the Keywords Plus (ID) category and 1370 keywords from the Author's Keywords (DE) category, indicating that this study covers a wide range of aspects in understanding the factors that influence AI adoption in academic environments.

Regarding author contributions, 1379 authors were involved in this study, of which 47 were single authors. However, only 51 documents were written by a single author, indicating that most research in this field is conducted collaboratively. This finding can be seen from the average number of authors per document, which reached 3.44, indicating a strong tendency towards academic collaboration. Furthermore, the level of international collaboration is also

quite high, with 34.7% of documents written by authors from more than one country, reflecting the global nature of research on AI in higher education.

In terms of document type, most of the publications in this dataset are journal articles, with a total of 402 documents. In addition, several documents are categorised as conference papers, with 58 documents indicating that research in this field is also widely presented in academic forums and international conferences. Several documents were also detected in unique categories such as "article article" (3 documents) and "conference paper article" (1 document), which are likely to be metadata duplication or misclassification in bibliometric processing.

This analysis showed that research on AI adoption intentions in higher education is a rapidly growing field with a broad scope and heavily supported by international collaboration. With a high annual publication growth rate and a high average number of citations per document, it can be concluded that this topic has a significant impact on the academic community and is likely to grow in the coming years. However, this study also shows that there is still room for further exploration, especially in integrating various theories and in-depth analysis of the social, psychological, and regulatory aspects that influence AI adoption in academia.

Network Analysis

The initial figure in the bibliometric analysis presents a network visualisation delineating the interrelationships among frequently occurring keywords in the literature focused on AI adoption intention within higher education as presented in figure 2. This visualisation maps the conceptual terrain and serves as a tool for identifying the principal clusters encapsulating the intellectual structure of research in this domain. By illustrating the interconnectedness of concepts and research topics, the network visualisation offers insights into the evolution of scholarly discourse over time (Saleem et al., 2023).

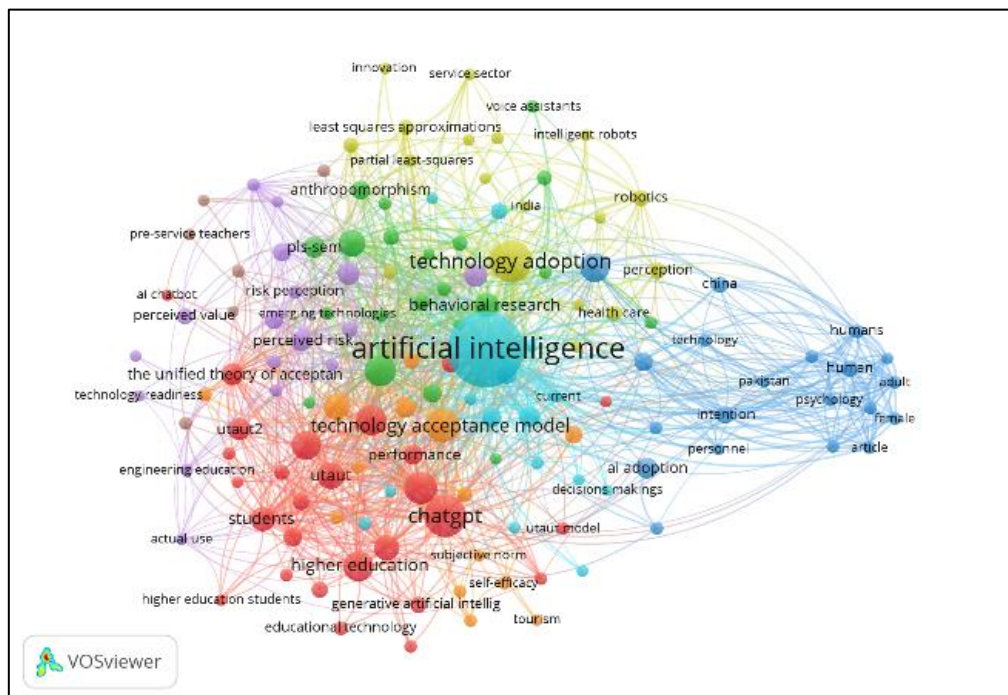


Figure 2. Network Visualisation

Upon close examination, several prominent clusters emerge, with larger, vividly coloured clusters indicating high-frequency research foci such as the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and various individual and organisational factors that shape AI adoption intentions. These clusters underscore areas of extensive scholarly attention and imply that methodological rigour and theoretical depth have predominantly centred around these paradigms (Ivanova et al., 2024). For example, the TAM and TPB frameworks have been widely adopted to examine the factors influencing the acceptance of AI-based technologies in higher education settings, forming a significant basis of the established literature (Abdekhoda & Dehnad, 2024).

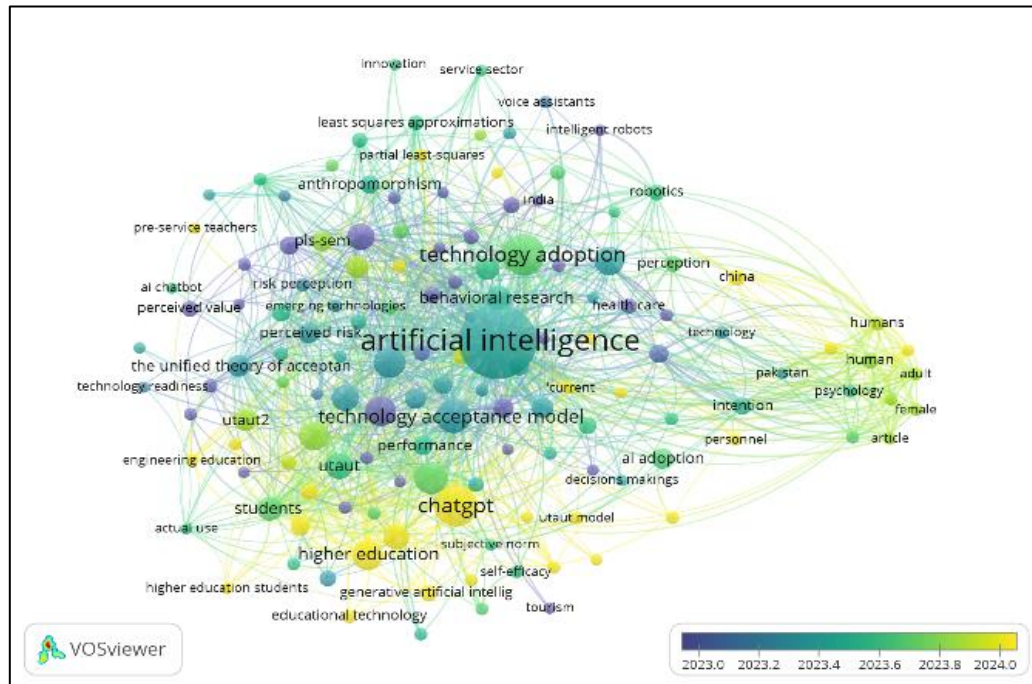
Furthermore, the diagram reveals meaningful inter-cluster connectivity, particularly between technology-based frameworks and behaviour-based approaches. This linkage underscores the multidisciplinary nature of AI adoption research, reflecting the convergence of technological innovation and behavioural theory in addressing practical challenges within higher education (Ivanova et al., 2024). Such interconnections suggest that the field is characterised by complementary perspectives, where technical efficacy is analysed alongside user perceptions and organisational readiness.

However, despite these connections, the network visualisation highlights a degree of fragmentation. Certain clusters exhibit limited connectivity, suggesting that while multiple theoretical frameworks coexist, integrative research that unifies these paradigms into comprehensive models is scarce. This observation reinforces a critical research gap—the absence of holistic conceptual mapping that could integrate diverse yet complementary theories underpinning AI adoption intentions in higher education (Zhao et al., 2024). The evident fragmentation signals that, while various dimensions of AI adoption have been studied, the literature lacks unified frameworks encompassing technology-oriented and socio-behavioural factors (Abdekhoda & Dehnad, 2024).

The network analysis thus validates the existence of distinct yet interrelated research areas while highlighting opportunities for future investigations. By bridging isolated clusters, researchers can develop more integrated frameworks that enhance theoretical coherence and address the multifaceted influences on AI adoption in higher education. Such integrative models could capture the interplay between established constructs like perceived usefulness and ease of use alongside emerging variables, including ethical considerations and user engagement (Saleem et al., 2023). Moreover, this comprehensive integration would facilitate a deeper understanding of how technological innovation, individual behaviour, and organisational dynamics converge, providing a foundation for academic inquiry and practical applications in educational technology.

Overlay Analysis

The overlay visualisation presented in Figure 3 offers a dynamic perspective on the temporal evolution of research trends in AI adoption intentions within higher education. This visualisation distinguishes established themes from emerging directions by employing a colour gradient to depict the relative age of key concepts. Darker hues represent older, well-established keywords—while lighter colours signal recent developments—thus facilitating an immediate understanding of the progression of research themes over time (Krishna et al., 2023).



This overlay visualisation reveals that early research predominantly focused on foundational constructs such as the Technology Acceptance Model (TAM) and perceived usefulness. These concepts, depicted in darker colours, have historically dominated discussions related to technology adoption in educational contexts (Acosta-Enriquez et al., 2024). Their prominence in early literature underscores the initial emphasis on technical and cognitive factors that drive AI acceptance among educators and learners. Conversely, lighter-coloured nodes in the visualisation highlight newer research directions. Recent studies have begun to explore diverse dimensions of AI integration, including the role of AI in enhancing learning experiences, its influence on student-instructor interactions, and the ethical considerations associated with its implementation in academic institutions (Krishna et al., 2023; Yan & Li, 2020).

This temporal mapping is instrumental in identifying a critical research gap: while numerous studies have concentrated on individual theoretical frameworks, there remains limited exploration of the interactions between these frameworks—particularly between technology-based and social behaviour-based approaches. The overlay analysis underscores the need for integrated models that capture the multifaceted nature of AI adoption intentions. This gap offers a rich avenue for future research to develop holistic frameworks that reconcile established paradigms with emerging perspectives, thus ensuring that theoretical development is as dynamic as the technological advancements it seeks to explain (Saleem et al., 2023).

Moreover, the overlay visualisation serves as a historical record and a strategic tool for forecasting future research directions. This method provides insight into shifting priorities within the academic community by clearly delineating the evolution of key terms. For example, as ethical issues and interpersonal dynamics of AI applications become more salient—evidenced by the emergence of related keywords in lighter colours—the overlay visualisation suggests that future research may increasingly emphasise interdisciplinary approaches. These

approaches could integrate insights from engineering, behavioural science, and ethics to address the complexities of AI implementation in higher education (Krishna et al., 2023; Yan & Li, 2020).

. As a result, researchers are better equipped to design studies that bridge the gaps between traditional technology acceptance models and contemporary challenges faced by academic institutions striving for digital transformation.

The overlay analysis offers a visually intuitive means of understanding how historical and emerging research trends in AI adoption intentions have evolved. It confirms that while early research focused on core constructs such as TAM and perceived usefulness, recent contributions have expanded the discourse to encompass issues related to ethical implications, interactive learning, and the broader impact on educational ecosystems. By leveraging such temporal insights, future research can be more strategic in formulating integrative conceptual models that address long-standing and novel challenges in implementing AI in higher education.

Density Analysis

As depicted in Figure 4, density visualisation offers a quantitative insight into the concentration and intensity of research activity on various concepts related to AI adoption intention in higher education. In such visualisations, lighter-coloured areas indicate topics that are highly researched and well-developed, whereas darker zones highlight areas that remain underexplored and may represent emerging fields or neglected research opportunities (López-Chila et al., 2024). This visualisation method is particularly useful in bibliometric studies because it translates large volumes of publication data into an easily interpretable research density map, thereby revealing established and nascent trends.

In the context of AI adoption in higher education, the density map indicates that key constructs such as "perceived usefulness," "perceived ease of use," and "technology adoption" occupy regions of high density. These constructs, central to the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB), have been extensively examined by researchers over the years (Banjarnahor, 2021; Martin, 2022). The pronounced focus on these functional aspects reflects a mature body of literature that has largely concentrated on understanding how technological attributes and user perceptions drive adoption. For instance, studies have consistently shown that AI systems' perceived benefits and usability are decisive factors in fostering user acceptance, a finding strongly supported by the high-density areas observed in our visualisation (Martin, 2022).

Conversely, the density analysis also reveals several underdeveloped zones marked by darker colours, indicating topics that have received relatively less scholarly attention. Areas such as the influence of user experience on AI utilisation, student involvement in the AI adoption process, and the impact of sustainability and ethical considerations in implementing AI in higher education are less densely populated (Fernandes et al., 2024). These gaps are critical because they suggest that while the literature has robustly addressed the functional dimensions of AI adoption, there remains limited exploration of how broader sociocultural and ethical factors shape adoption intentions in academic settings (Khanfar et al., 2024). The sparse density in these areas underlines a significant research gap—a need for a more comprehensive, integrative approach that not only considers traditional technology-based factors but also incorporates social, cultural, and regulatory dimensions.

This observation is consistent with recent studies that have advocated for a holistic framework to understand AI adoption. Fernandes et al. (2024) emphasised that sustainability and ethical concerns are increasingly important as educational institutions strive for digital transformation while adhering to social responsibility. Furthermore, Khanfar et al. (2024) argued that future research should bridge the divide between the well-documented technological determinants and underexplored humanistic factors. Such an integrative approach would enrich our understanding by incorporating student engagement, experiential learning, and ethical implications into the conceptual models traditionally dominated by TAM and TPB constructs.

The contribution of the results of this study to the theories used is very significant. In the context of TAM, these findings confirm that perceived usefulness and perceived ease of use are still the main factors influencing the intention of AI adoption in higher education. However, the results also suggest that this model needs to be expanded by taking into account new factors such as trust in AI and the social impact it causes. In the Unified Theory of Acceptance and Use of Technology (UTAUT), the results show that performance expectations and social influence are still the dominant factors in AI adoption. However, the existence of factors such as AI ethics regulations and policies in education suggests that this theory needs to be updated to be more relevant to current AI developments. The Diffusion of Innovation (DOI) theory was also validated in this study, where the relative superiority of AI in improving academic efficiency was the main factor influencing its adoption. However, the complexity of AI is still a major challenge that hinders the diffusion of this technology in higher education.

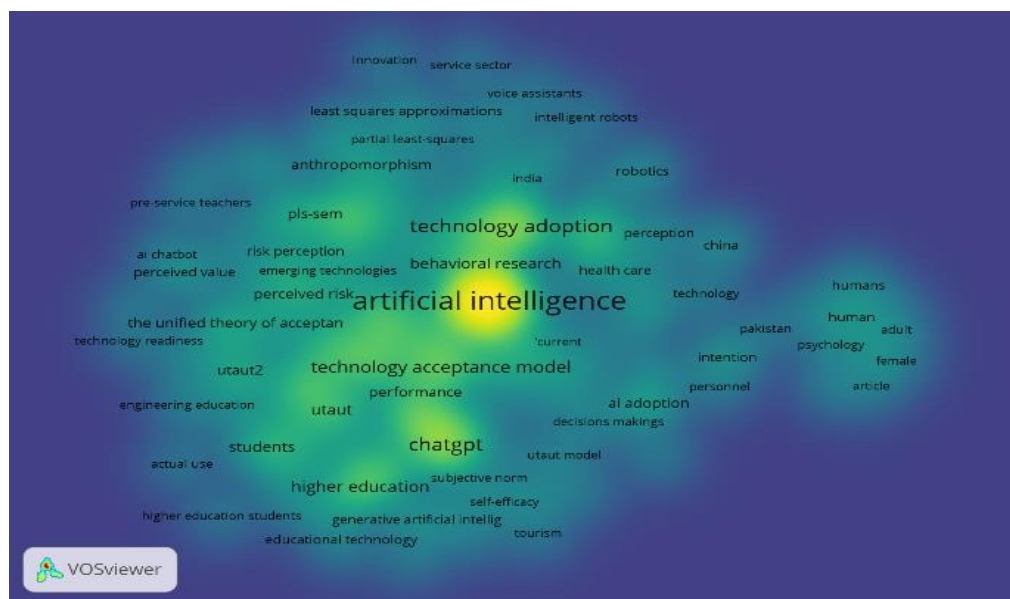


Figure 4. Density Visualisation

The implications of these findings are twofold. First, the high-density regions confirm the established reliability of studies on perceived usefulness, ease of use, and technology adoption, validating decades of empirical research in this area. Second, low-density areas point to emerging trends and potential avenues for future research. Researchers can leverage these visual cues to identify topics that warrant deeper inquiry. For instance, further studies might explore how nuanced aspects of user experience—such as emotional response, cognitive load,

or the perceived fairness of AI systems—influence the overall adoption intentions. Such investigations could lead to a more refined conceptual model that synthesises technology-centric and human-centred factors (Fernandes et al., 2024; Khanfar et al., 2024).

Moreover, density visualisation is a strategic tool for both academic and practical purposes. It provides a clear map of the research landscape for academics, enabling scholars to identify gaps and propose novel research questions that address these voids. For practitioners and institutional decision-makers, understanding the density of research on specific constructs offers insights into the maturity of various dimensions of AI adoption. This implication can guide policy formulation and the development of targeted strategies to address underdeveloped areas, thereby fostering a more sustainable and ethically grounded implementation of AI in higher education (López-Chila et al., 2024).

This study relies exclusively on the Scopus database, which may introduce database bias by excluding non-indexed or region-specific journals. The time window (2010–2024) omits the very latest in-press research. Finally, our analysis did not differentiate by journal quartile (Q1–Q4), which could affect the representativeness of citation impact.

CONCLUSION

This study analyses research trends and developments related to AI adoption intention in higher education through a bibliometric approach. Using data from Scopus and the PRISMA method, this study successfully identified publication patterns, conceptual network structures, and topic evolution in AI adoption intention studies. The results show that the number of publications in this field has experienced significant growth in the last two decades, reflecting the increasing academic attention to implementing AI in education.

The main findings from the network visualisation reveal that research in this area is still fragmented, with major clusters reflecting the use of theories such as TAM and TPB. However, the lack of connections between clusters suggests that the integration of theories in the study of AI adoption intention is still limited. The overlay visualisation shows that early research focused more on the technical aspects of AI and technology acceptance models, while in recent years there has been an exploration of the ethical, trustworthy, and regulatory aspects of AI. The density visualisation confirms that while topics such as perceived usefulness and perceived ease of use have been widely researched, AI's social and policy aspects remain under-explored and require further research.

The contribution of this study to technology adoption theories is significant. In the context of TAM, the results show that perceived usefulness and perceived ease of use remain the main factors in AI adoption intention, but there is a need to extend this model by considering new factors such as trust in AI and its social impact. TPB has also been confirmed as a relevant theory, with the findings that Performance expectations and social influence play an important role in AI adoption. However, this model has not sufficiently considered AI regulation and policy factors.

With these findings, further research will explore social, policy, and ethical factors in AI adoption in higher education. In addition, a more holistic approach is needed to understand AI adoption by integrating various theories used separately in previous studies.

In conclusion, our bibliometric mapping of AI adoption in higher education (2010–2024) reveals both a rapid growth in core TAM/TPB research and emerging ethical and policy concerns. However, findings must be interpreted in light of Scopus-only coverage and the exclusion of in-press studies. Future work should extend the dataset to include other databases

(e.g., Web of Science), disaggregate by journal quality (Q1–Q4), and explore longitudinal case studies to validate the observed thematic shifts.

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