Advances in Consumer Research
https://acr-journal.com/
Volume-3 | Issue-11 |0ct: 2026
Original Researcher Article

Exploring the Adoption of AI-driven Pedagogical Tools by Teachers- Trainers in India's Higher Education Sector

Sonali Beri[1], Dr. Tooba Bilgrami[2], Dr. Sumit Tomar[3], Dr. R. Priya[4]
[1]Assistant Professor Ram Charan School of Leadership MIT World Peace University, Pune, India
Email: sonaliberi9@gmail.com
[2] Assistant Professor
Christ University, Pune, India
Email: toobabilgrami@gmail.com
[3] Assistant Professor
Ram Charan School of Leadership
MIT World Peace University, Pune, India
Email: sumittomar0000@gmail.com
[4] Dean & Professor
School of Commerce and Management
Sanjivani University, Kopergaon, India
Email: yaprimba@gmail.com

ABSTRACT
Objective:The use of AI tools is becoming integrated into teaching, training and administrative operations in Indian higher education. This research addresses factors that influence behavioral intention to adopt AI-enabled tools for teaching and training for teachers and organizational stakeholders in Indian higher education.
Design/methodology/approach: Guided by the Technology Organization Environment (TOE) framework, a comprehensive adoption model was proposed and tested by integrating the technological, organizational and environmental determinants. Survey data were collected from 680 teachers and academic decision makers across Indian universities and colleges, which were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM).
Findings: The findings suggest that the intention to adopt AI are primarily driven by technological capability factors, specifically perceived intelligence and perceived interactivity. Organisational readiness and top management support also significantly influence adoption intention. From the environmental perspective, vendor support and competitive pressure showed a significant positive influence while perceived benefit and perceived risk were not found to influence adoption intention significantly, signaling a shift from outcome based appraisal towards the implementation issues in the decision of AI adoption.
Originslity/Value: Three original contributions are identified in this research: First, it expands the scope of inquiry in the area of AI adoption in higher education from students and broad faculty members to teacher-trainers which is one of the critical yet under-researched stakeholders who ultimately determine the future pedagogy; Second, it advances the existing T-O-E framework by adding specific technological characteristics associated with AI in explaining smart system adoption; Finally, it provides a unique empirical data set from a developing country context thus contributing to the external validity of AI adoption theories.
Keywords: Artificial intelligence adoption; Higher education; TOE framework; Faculty perspective; PLS-SEM.

1. INTRODUCTION

As higher education systems undergo rapid digital transformation, Artificial Intelligence (AI) is emerging as a critical technological driver reshaping teaching practices, learning environments, and institutional decision-making (Dwivedi et al., 2021; Zawacki-Richter et al., 2019; Holmes et al., 2019). AI has become one of the most influential technological developments shaping contemporary societies and organizations (Brynjolfsson & McAfee, 2017; Dwivedi et al., 2021; Davenport & Ronanki, 2018). While no universal definition for AI has been agreed upon, it is generally described as a class of technologies that learns from data, adapt to new inputs and can perform tasks typically requiring human intelligence (Russell & Norvig, 2021; Kaplan & Haenlein, 2019). Advances in machine learning, data analytics, and computing have sped up the adoption of AI in various sectors including healthcare, banking and finance, transportation and public services (Brynjolfsson & McAfee, 2017; Dwivedi et al., 2021; Davenport & Ronanki, 2018; Jordan & Mitchell, 2015). As a result, it is one of the key technologies contributing to the Industry 4.0 revolution, which allows for decision making, automation of complex tasks, and data-driven knowledge,

and leads to the development of organizational capabilities and innovation (Akter et al., 2022; Soni et al., 2020; Brynjolfsson & McAfee, 2017).

In recent years, this technology revolution has transformed higher education systems with universities and colleges exploring the integration of AI-enabled technology in teaching, learning and administrative activities (Zawacki-Richter et al., 2019; Bond et al., 2023; Holmes et al., 2019). From intelligent tutoring systems, conversational agents, learning analytics, to adaptive learning systems, such technologies enable educational institutions to leverage large datasets for personalized learning experience according to individual student needs (Zawacki-Richter et al., 2019; Hwang et al., 2020; Winkler & Sllner, 2018; Luckin et al., 2016). They can improve teaching efficiency, provide a foundation for pedagogic decision-making, enhance student engagement, and offer timely feedback and support for students' learning (Chassignol et al., 2018; Hwang et al., 2020; Bond et al., 2023; Holmes et al., 2019). It is apparent that AI technology has become one of the essential enablers of digital transformation in higher education.

The integration of AI technologies in higher education, however, still encounters challenges alongside opportunities. Issues such as algorithmic bias, opacity of automated decision-making, data privacy and ethical governance have sparked debates on responsible adoption of AI in education (Williamson & Eynon, 2020; Dwivedi et al., 2021; Floridi et al., 2018). The implementation of new technology, especially AI, requires significant investment of technological infrastructure, capabilities and organizational change processes (Akter et al., 2022; Davenport & Ronanki, 2018; Dwivedi et al., 2021). Hence, institutions need to make informed decisions about their adoption by weighing up the opportunities with the risks (Dwivedi et al., 2021; Williamson & Eynon, 2020; Holmes et al., 2019).

Such considerations reveal that AI adoption is more than a simple technological choice but a multifaceted process involving technological, organizational, and environmental aspects (Zawacki-Richter et al., 2019; Bond et al., 2023; Dwivedi et al., 2021).

Although AI has attracted much attention in educational research, there has been limited literature discussing the technological dimension of AI technologies, pedagogical aspect, user experience and their technological nature (Zawacki-Richter et al., 2019; Bond et al., 2023; Hwang et al., 2020). While such research has contributed to the understanding of potential benefits of AI-enhanced learning environment, the institutional and organizational factors affecting the decisions to adopt technologies by higher education institutions are largely overlooked (Bond et al., 2023; Dwivedi et al., 2021; Holmes et al., 2019). Universities are complex social structures where the implementation of new technology decisions can depend not only on technology's potential benefits but also on institutional readiness, leadership support and competitive and technological pressures (Akter et al., 2022; Zhai et al., 2021; Oliveira & Martins, 2010). In this respect, institutional technology adoption decisions require an organizational perspective (Dwivedi et al., 2021; Awa & Ojiabo, 2016).

However, despite rapid growth in research related to AI in education, there have been limited empirical studies focusing on institutional decision-making regarding AI adoption in higher education (Zawacki-Richter et al., 2019; Bond et al., 2023; Holmes et al., 2019). Researchers have traditionally adopted individual-level technology adoption models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) to test the behavioral intention factors impacting the technology adoption of the end-user (Davis, 1989; Venkatesh et al., 2003; Venkatesh et al., 2012). However, the limitation of these models are that they do not sufficiently explain the institutional and environmental factors shaping organizational adoption decisions (Dwivedi et al., 2021; Bond et al., 2023). With universities investing in new digital technologies to adapt to a rapidly changing educational landscape, there is a growing demand for theoretical frameworks that explain institutional decision-making on AI adoption (Akter et al., 2022; Zhai et al., 2021; Oliveira & Martins, 2010).

To bridge the research gap, the current study extends the TOE framework to examine the determinants of AI adoption in higher education institutions. The TOE framework implies that technology adoption is governed by technological context, organizational context, and environmental context (Depietro et al., 1990). This framework has been widely used in information systems literature to explain the adoption of technologies (e.g. Cloud computing, big data analytics, industry 4.0 etc) in organizational setting (Masood & Egger, 2019; Awa & Ojiabo, 2016). Very few studies have adopted this framework to analyze AI adoption in higher education by examining AI-specific technological constructs such as perceived intelligence and perceived interactivity in addition to other technological attributes (Dwivedi et al., 2021; Bond et al., 2023; Holmes et al., 2019).

Therefore, the present study further develops the TOE framework by incorporating the two AI-specific technological attributes – perceived intelligence and perceived interactivity along with technological, organizational, and environmental constructs. The study intends to examine the factors impacting the adoption of AI in higher education institutions.

The current study has several contributions: First, it addresses a gap in current AI-in-education research by shifting the focus from individual user perspective to organizational-level innovation adoption (Dwivedi et al., 2021; Bond et al., 2023). Second, by integrating AI-specific technological dimensions into the TOE framework, the study extends the literature on how the adoption decisions of AI are influenced by its specific characteristics and that how it differs from traditional information systems (Akter et al., 2022; Zawacki-Richter et al., 2019; Holmes et al., 2019). Third, it provides useful recommendations to institutional decision-makers, policymakers, and educational technology providers in integrating AI technologies into higher education institutions.

2.LITERATURE REVIEW

2.1Artificial Intelligence in Higher Education

In comparison to information technology, Artificial Intelligence is an intelligent technology which not only can be applied for storing, accessing and transmitting information but also helps users learning from big data and making a wise and adaptive decision. Therefore, it can move beyond information technology to intelligent information provision and assistance in teaching and learning processes (Brynjolfsson & McAfee, 2017; Holmes et al., 2019). AI-enabled intelligent tutoring systems, adaptive learning platforms and conversational agents not only help students learning from individual responses based on their behaviors and customize the content of teaching accordingly but also support them with timely learning feedback and interaction to improve learning efficiency and increase engagement (Woolf, 2010; Luckin et al., 2016; Zawacki-Richter et al., 2019; Marcos, 2026). They can effectively facilitate teachers identifying students' learning needs more precisely and providing intervention accordingly to improve students' academic performance.

Despite benefits mentioned above, AI adoption raises concerns regarding algorithmic bias, opacity of automated decision-making, data privacy, ethical governance, etc. The reliance on AI systems
necessitates the establishment of organizational mechanisms that are fair, accountable, transparent and trustworthy (Baker & Smith, 2019; Dwivedi et al., 2021). Universities will need to strike a balance between the adoption of advanced technologies and the governance policies on the responsible use of AI.

2.2 AI Adoption in Educational Contexts

Studies on AI adoption in education have significantly contributed to understanding the benefits of AI for personalization, automation, and assisting instructional decision making (Zawacki-Richter et al., 2019; Bond et al., 2023). AI systems analyze learning data and provide timely support to students while enabling teachers to have personalized interaction with learners and support data-driven decision-making.

The pandemic caused the expansion of digital learning technologies and AI in the educational field. This had significantly increased the demand for AI tools to support online and blended learning modes of teaching and learning (Carrillo & Flores, 2020). The rise of conversational agents and generative AI in particular is a phenomenon that could drastically alter how students perform tasks such as researching, writing, and problem-solving and supports the acquisition of self-learning strategies (Mittal et al., 2021; Chan & Hu, 2023). While the potential risks and challenges associated with AI (e.g. Academic dishonesty, over-dependence, reliability and accuracy issues) urge for governance guidelines, the decision for adopting AI in higher education also involves more than that and can be influenced by the technology itself and the surrounding environment and the organization.

2.3 Limitations of Individual-Level Technology Adoption Models

Existing educational technology research primarily uses individual-level theoretical models such as TAM and UTAUT (Davis, 1989; Venkatesh et al., 2003; Venkatesh et al., 2012) to investigate technology adoption behavior. TAM explains individual's behavioral intention to use technology by
performance expectancy and effort expectancy factors (Davis, 1989), whereas UTAUT extends this to include performance expectancy, social influence, effort expectancy, and facilitating conditions (Venkatesh et al., 2003). While these models are beneficial for understanding individual's attitude toward technology, they do not sufficiently explain the organizational and environmental issues influencing technology adoption by educational institutions. Recent systematic reviews on AI in education highlighted the need for multi-level factors which incorporate the interplay between technology, organization and environment for the analysis of AI adoption (Bond et al., 2023; Dwivedi et al., 2021). To address this shortcoming, TOE framework offers a more comprehensive viewpoint for explaining innovation adoption at the organizational level.

2.4 The Technology Organization Environment (TOE) Framework

The Technology Organization Environment (TOE) framework was introduced by Depietro et al. (1990) and proposes three contexts for technological innovation adoption within organizations: technological, organizational, and environmental contexts. Each of these contexts is associated with specific factors that influence the adoption decisions.

Technological context involves factors relating to technology characteristics such as perceived benefits, compatibility and complexity. Organizational context refers to internal organizational factors such as organizational resources, infrastructure and leadership support; finally, environmental context comprises external influences such as competitive pressures and vendors. The TOE framework has been broadly adopted in various information system adoption studies across a wide range of fields (Masood & Egger, 2019; Awa & Ojiabo, 2016). However, while the existing literature examines the use of the TOE framework for traditional information systems adoption, less focus has been placed on AI adoption at the university level, particularly with regard to specific technological characteristics that describe intelligent systems (Dwivedi et al., 2021; Bond et al., 2023; Holmes et al., 2019).

2.5 Technological Determinants of AI Adoption

Within the technological dimension of TOE, particular characteristics of AI play an important role. Perceived intelligence refers to a user's perception of a technology's capabilities and sophistication in mimicking human-like behaviors such as learning and adaptation (Warner & Sugarman, 1986; Weiss & Bartneck, 2015). An AI technology that demonstrates intelligence can be perceived as valuable and effective in providing support for learning and education (e.g., in analyzing learning

patterns, suggesting remedial actions, and offering personalized feedback) and hence encourages its adoption by users (Hwang et al., 2020). Therefore, higher the level of perceived intelligence by a user, the greater will be his or her adoption intention towards AI technologies in education. Hence, perceived intelligence is expected to positively influence the adoption intention of AI technologies in higher education institutions.

In addition to the cognitive capabilities, an interactive system can support collaborative interaction and effective user engagement (McMillan & Hwang, 2002; Park & Yoo, 2020). Higher levels of perceived interactivity in an AI technology is thought to increase the feeling of engagement and a greater willingness to adopt such technology. For example, intelligent tutoring systems and chatbots can interact with students through conversation and guide them throughout the learning process (Hwang et al., 2020). This enables a user-friendly learning experience that encourages greater use and adoption of AI systems in the educational setting. Hence, perceived interactivity is expected to positively influence the adoption intention of AI technologies in higher education institutions.

Perceived benefits refer to the degree to which an organization believes adopting technology will have an advantage in productivity, performance or other benefits (Phillips et al., 1994; Yang et al., 2022). Organizations adopting a technology if it improves its operation or the performance can lead to an increased probability for the adoption. In the context of education, adopting an AI technology, for example, may bring advantages of efficiency, personalization of learning experience and data-driven

insights into students' learning patterns and may promote higher learning outcomes and improved teaching effectiveness. Therefore, perceived benefits are hypothesized to positively influence the adoption intention of AI technologies in higher education institutions.

Conversely, Perceived risk is the uncertainty and concern about potential losses or hazards arising from the use of a technology (Im et al., 2008; Ho et al., 2017). Higher levels of perceived risks can make users to hesitant to adopt new technology. Similarly, high levels of Perceived risk such as security, privacy and reliability concerns of AI system might hinder higher education institutions to adopt this new technology. Therefore, perceived risk is hypothesized to negatively influence the adoption intention of AI technologies in higher education institutions.

2.6 Organizational Determinants of AI Adoption

Organizational Readiness: This concept refers to the existence of both technical readiness and human readiness to embrace a new technology (Chwelos et al., 2001; Abed, 2020). IT Infrastructure, human skills and the resources to allocate to implement new technology and to create organizational and process capacity needed to embrace new technologies such as data security measures and sufficient storage capacity will be of prime importance. The extent to which the organization has IT infrastructure to support a new technology and the available of human resource and skill sets are essential for its adoption. Hence, organizational readiness is expected to have a positive impact on the intention to adopt AI technologies in higher education institutions.

Top management support: This includes the active participation of top managers in defining strategic goals, making decisions and facilitating and supporting the adoption of technology (Rodrguez et al., 2008; Felekoglu & Moultrie, 2014). Management can facilitate and support the successful implementation of new technologies by influencing the organization's resource allocation and shaping strategic directions. Top management support is an important prerequisite for facilitating the adoption of innovations within an organization by reducing resistance and driving change initiatives. Therefore, top management support is expected to positively influence the intention to adopt AI technologies in higher education institutions.

2.7 Environmental Determinants of AI Adoption

Vendor support: Technology vendors can provide assistance in terms of implementing the technology, troubleshooting problems during operation and maintaining the technology (Premkumar & Roberts; Pillai & Sivathanu, 2020). Higher education institutions are dependent on vendors in installing and maintaining advanced technologies such as AI applications due to the technical complexity of these technologies and lack of sufficient technical staff on site. The extent of the vendor support is important as it can alleviate technical uncertainty in terms of operating the new system and can ease up the implementation of new technology in higher education institutions. Hence, vendor support is expected to positively influence the intention to adopt AI technologies in higher education institutions.

Competitive pressure: Competitive pressure occurs when an organization perceives that not adopting new technologies may create an advantage for competitors and thus, is induced to adopt new technologies (Oliveira & Martins, 2010; Hungund & Mani, 2019). Higher education institutions need to face competition both from domestic and foreign higher education providers. Adopting a new technology such as AI technology could be a strategic move for them to differentiate themselves from the competition by enhancing teaching quality, student services, and overall reputation in the education field. Therefore, competitive pressure is expected to positively influence the adoption intention of AI technologies in higher education institutions.

The extant literature review clearly points out that there are gaps in understanding institutional-level factors impacting AI adoption by higher education institutions, whereas most studies address technology acceptance issues at the user level, using models such as TAM and UTAUT. While the TOE framework

has been widely employed to explain the adoption of technological innovations, very few studies have adopted this framework for analyzing AI adoption in higher education institutions. Furthermore, few previous studies include the technological characteristics of AI such as perceived intelligence and perceived interactivity for the adoption behavior analysis. Therefore, this study intends to test a theoretical model based on the TOE framework

by incorporating unique AI-specific technological factors namely perceived intelligence and perceived interactivity, together with the traditional technological, organizational and environmental factors on the intention to adopt AI technologies in Indian higher education institutions.

Hypotheses

Technological Context

H1: Perceived intelligence positively influences the adoption intention of AI technologies in higher education institutions.

H2: Perceived interactivity positively influences the adoption intention of AI technologies in higher education institutions.

H3: Perceived benefits positively influences the adoption intention of AI technologies in higher education institutions.

H4: Perceived risk negatively influences the adoption intention of AI technologies in higher education institutions.

Organizational Context

H5: Organizational readiness positively influences the adoption intention of AI technologies in higher education institutions.

H6: Top management support positively influences the adoption intention of AI technologies in higher education institutions.

Environmental Context

H7: Vendor support positively influences the adoption intention of AI technologies in higher education institutions.

H8: Competitive pressure positively influences the adoption intention of AI technologies in higher education institutions.

3. RESEARCH METHODOLOGY

This study employs a quantitative research design to investigate the relationships between the variables stated in the conceptual model. The primary data were collected using a structured questionnaire distributed both face-to-face and through online surveys. Utilizing multiple modes for the survey helped increase response rate, minimize non-response bias and effectively reach dispersed institutions to enhance data representation and generalizability.

The research design included Questionnaire Design, sampling process and data collection procedure which enabled a precise and rigorous empirical study. Particular attention was given to design a measure to effectively determine the relationships between technological, organizational and environmental dimensions which is included in the proposed model and variables. The central aim of the analysis was to understand the relationships between the constructs from technological, organizational and environmental context. The study examines 'AI Adoption Intention', which represents the predisposition to adopt and utilize an AI technology by teachers and university stakeholders. Partial Least Squares Structural Equation Modelling (PLS-SEM) was selected to investigate the relationships due to its effectiveness in theory development and in the context of complex models.

3.1 Research Instrument

A comprehensive audit of the Technology-Organization-Environment (TOE) system served as the theoretical foundation of the research instrument. Each estimation scale was meticulously fine-tuned based on well-established writings from a range of fields of literature including perceived insights (Amherst and Tussyadiah, n.d.; Bartneck et al., 2009; Pillai and Sivathanu, 2020a), perceived benefits (Pillai et al., 2022; Lin, 2014; Oliveira and Martins, 2010a), perceived interactivity (Qalati et al., 2021), perceived risk (Shi et al., 2020), organizational status (Abed, 2020), top administration support (Alam et al., 2016), seller support (Ghobakhloo et al., 2011), and competitive pressures (Cruz-Jesus et al., 2019). These theoretical concepts were refined and adapted for this particular investigation. Before proceeding with data collection, six experts with prominent administrative positions in higher education were selected as members of the panel to conduct a thorough review of the research instrument. The experts were fully briefed regarding the objective of the research. Their suggestions were incorporated into the final design of the questionnaire so as to improve its face validity. An existing, well-validated questionnaire on the adoption of technology and Artificial intelligence was adapted to develop the present questionnaire for research purposes. All constructs are reflected measures based on the Technology-Organization-Environment (TOE) model and these include perceived intelligence (PI), perceived benefits (PB), perceived interactivity (PIN) and perceived risk (PR). PI is measured on a 5 item Likert scale derived from Amherst and Tussyadiah (n.d.), Bartneck et al. (2009) and Pillai and Sivathanu (2020a).PB and PIN were measured using items adapted from Lin (2014), Oliveira and Martins (2010a), and Qalati et al. (2021). PR was operationalized using three items adapted from Shi et al. (2020).The organizational dimension comprised Organizational Readiness (OR) and Top Management Support (TMS), measured using items adapted from Abed (2020) and Alam et al. (2016). The environmental dimension included Vendor Support (VS) and Competitive Pressure (CP), adapted from Ghobakhloo et al. (2011), Pillai et al. (2022), Cruz-Jesus et al. (2019), and Gangwar et al. (2015). All items were measured using a five-point Likert scale (1 = strongly disagree, 5 = strongly agree) and pilot tested prior to full-scale data collection.

AI Adoption Intention was measured using a reflective scale adapted from Pillai and Sivathanu (2020). The items were contextualized to the higher education sector and measured on a five-point Likert scale. In the present study, faculties and trainers within higher education setting that currently have been adopting the AI-based educational tools like chatbots, mobile learning apps and interactive platforms in their teaching and training strategies was focused. In order to test the framework designed, partial Least Squares Structural Equation Modeling was applied to analyze data collected. 3.2 Sampling Methods Quantitative study A structured questionnaire was employed for collection of data and convenience sampling was again adopted. The survey was carried out for 11 months from faculties of public and private universities, post graduate institutions, research centers across cities of

India. Pune, Mumbai, Chandigarh, New Delhi, Chennai and Ahmedabad were the major metropolitan cities involved and only respondents with experience using AI based educational tools were involved.

Table 1: Measurement Model Summary

Main Construct	Type	Indicators / Items	Reference
Perceived Intelligence (AVE=0.744, CR=0.916, α=0.835)	Reflective	I believe AI in education is capable. I believe AI in education is knowledgeable. I believe AI in education is accountable. I believe AI in education is intelligent. I believe AI in education is reasonable.	Amherst & Tussyadiah; Bartneck et al. (2009); Pillai & Sivathanu (2020)
Perceived Benefits (AVE=0.708, CR=0.860, α=0.829)	Reflective	AI enhances the quality of education. AI increases the overall efficiency of the education process. AI accelerates the educational process.	Pillai et al. (2022); Lin (2014); Oliveira & Martins (2010)
Perceived Interactivity (AVE=0.815, CR=0.930, α=0.886)	Reflective	AI facilitates interactive communication with users. AI provides interactive systems for value creation with users. AI encourages engagement with users.	Qalati et al. (2021)
Perceived Risk (AVE=0.730, CR=0.872, α=0.811)	Reflective	Using AI in education involves risks. There is a potential for data loss when applying AI in education. It is unlikely to manage all students effectively with AI.	Shi et al. (2020)
Organization Readiness (AVE=0.815, CR=0.865, α=0.863)	Reflective	The organization has the financial capacity to implement AI in education. The organization possesses the technological resources needed to adopt AI. The organization has strong internet connectivity. Most employees have unrestricted access to computers. Most employees are proficient in using computers.	Abed (2020)
Top Management Support (α=0.820)	Reflective	Top management actively supports the adoption of AI in education. Top management has committed sufficient resources for the implementation of AI in education. Top management is aware of the advantages of AI in education.	Alam et al. (2016)
Vendor Support (AVE=0.706, CR=0.851, α=0.804)	Reflective	AI vendors would offer technical support to educational institutions. AI vendors would provide essential training on AI operations for educational institutions. AI vendors offer free training to promote AI.	Pillai et al. (2022); Ghobakhloo et al. (2011)
Competitive Pressure (AVE=0.670, CR=0.890, α=0.765)	Reflective	AI vendors actively engage in marketing AI. Companies believe that AI in education affects competition within their industry. Our company feels pressured by competitors to adopt AI systems. Some of our competitors have already implemented AI systems. Our competitors recognize the importance of AI and are utilizing it in their operations. Our company would have faced a competitive disadvantage if AI had not been adopted.	Cruz-Jesus et al. (2019); Gangwar et al. (2015)
AI Adoption Intention (AVE=0.742, CR=0.920, α=0.883)	Reflective	I intend to adopt AI-based tools for teaching and learning activities. I plan to use AI technologies regularly for academic tasks. My institution is likely to adopt AI-based educational tools soon. I am willing to integrate AI applications into my teaching practices. I expect AI-based systems to be widely used in education in the future.	Pillai & Sivathanu (2020)

1110 questionnaires were distributed among samples and 995 responses were obtained, out of which 680 are valid ones after critical screening and a reasonable response rate achieved.

Non-response bias analysis

For assessing non-response bias, we compared early (249) and late (431) respondents by t-test (p=0.37), according to Armstrong and Overton (1977) and Tsou and Hsu (2015). Results confirmed no non-response bias and hence the sample is representatives.

Common method bias and Endogeneity

To avoid common method bias (CMV), we conducted a Harman's single factor test, which revealed variance at 29.48%, which is less than the suggested limit (Hair et al., 2017). Moreover, endogeneity may exist since the structure of model is recursive, so to address this endogeneity, Ramsey Regression Equation Error Test was performed (Lai et al. 2018) and checked model robustness.

Data analysis & Results

The respondents' demographic profile depicts gender-wise 44% females and 56% males, while hierarchical strata show 32% senior-level, 38% mid-level, and 30% junior-level faculty and trainers. Regarding technology usage, 49% of faculty and trainers currently use AI-based tools for teaching and training, while the other 51% use alternative advanced technologies like chatbots and interactive platforms for a variety of functions, from teaching to feedback mechanisms to research and development. AI-based educational tools include prominent brands such as Botsify, MakerBot, QuillBot, Jill Watson (IBM), Michelle Chatbot (Acquire), Teaching Community Assistant (Microsoft), Dialogflow (Google), Ada, Kuki Chatbot, and Watson Assistant (IBM). The study depicts the use of these advanced technologies, with 59% of samples using them in the last 6 months and 41% using them for more than 6 months. The samples come from 26 universities and 54 colleges (institutions) and were drawn from major cities across India, including Pune, Mumbai, Chandigarh, New Delhi, Chennai, and Ahmedabad.

Measurement model

PLS-SEM technique has been employed for analysis of relationships between exogenous and endogenous latent construct and exogenous variables in the designed model. PLS-SEM is a technique that makes less strict requirements about the distribution of the data and offer more flexibility to models than covariance-based SEM approach (Henseler & Chin, 2010). It determines latent construct using indicator variables on a variance based approach like ordinary least squares regression (Chin et al., 2008). Thus, PLS-SEM is applicable for models with number of variables and heterogeneous sample size as used in research in social science and educational technology fields (Hair et al., 2017).

Results of the measurement model revealed high internal consistency and reliability for all constructs. All Cronbach's alpha values exceed the generally accepted minimum threshold value 0.80 and for composite reliability (CR) was greater than 0.70 (as show in Table 3), indicating that scales possess construct reliability (Nunnally, 1978). With average variance extracted (AVE) for all constructs was above 0.50; convergent validity is achieved (Guadagnoli & Velicer, 1988; Hair et al., 2017).

Table 2 Construct Reliability and Validity

Construct Reliability and Validity

Matrix | Cronbach's Alpha | rho_A | Composite Reliability | Average Variance Extracted (AVE) | Copy to Clipboard: | Excel Format | R Format

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
PERCEIVED RISK	0.871	0.872	0.921	0.795
COMPETITIVE PRESSURE	0.885	0.887	0.916	0.685
ADOPTION INTENTION	0.968	0.968	0.975	0.886
ORGANISATION READINESS	0.934	0.935	0.950	0.790
PERCEIVED BENEFITS	0.856	0.860	0.913	0.777
PERCEIVED INTELLIGENCE	0.910	0.911	0.933	0.735
PERCEIVED INTERACTIVITY	0.904	0.905	0.940	0.839
TOP MANAGEMENT SUPPORT	0.810	0.815	0.888	0.725
VENDOR SUPPORT	0.865	0.866	0.918	0.788

Table 3 Discriminant Validity Table 3.1

Discriminant Validity

Fornell-Larcker Criterion | Cross Loadings | Heterotrait-Monotrait Ratio (HTMT) | Heterotrait-Monotrait Ratio (HTMT) | Copy to Clipboard: Excel Format R Format

	PERCEIVE...	COMPETITI...	ADOPTION ...	ORGANISA...	PERCEIVED ...	PERCEIVED ...	PERCEIVED ...	TOP MANA...	VENDOR S...
PERCEIVED RISK									
COMPETITIVE PRESSURE	0.497								
ADOPTION INTENTION	0.493	0.557							
ORGANISATION READINESS	0.513	0.543	0.567						
PERCEIVED BENEFITS	0.498	0.494	0.546	0.514					
PERCEIVED INTELLIGENCE	0.550	0.512	0.594	0.484	0.507				
PERCEIVED INTERACTIVITY	0.512	0.522	0.645	0.573	0.564	0.517			
TOP MANAGEMENT SUPPORT	0.495	0.539	0.603	0.514	0.533	0.498	0.574		
VENDOR SUPPORT	0.509	0.536	0.641	0.521	0.531	0.530	0.492	0.536	

Table 3.2

Discriminant Validity

Fornell-Larcker Criterion | Cross Loadings | Heterotrait-Monotrait Ratio (HTMT) | Heterotrait-Monotrait Ratio (HTMT) | Copy to Clipboard: Excel Format R Format

	PERCEIVE...	COMPETITI...	ADOPTION ...	ORGANISA...	PERCEIVED ...	PERCEIVED ...	PERCEIVED ...	TOP MANA...	VENDOR S...
PERCEIVE...	0.892								
COMPETITI...	0.437	0.828							
ADOPTION ...	0.453	0.516	0.941						
ORGANISAT...	0.463	0.494	0.539	0.889					
PERCEIVED ...	0.430	0.431	0.498	0.460	0.881				
PERCEIVED ...	0.490	0.460	0.558	0.447	0.448	0.858			
PERCEIVED ...	0.454	0.468	0.604	0.527	0.497	0.469	0.916		
TOP MANA...	0.415	0.457	0.535	0.448	0.445	0.427	0.493	0.851	
VENDOR SU...	0.442	0.470	0.587	0.469	0.457	0.471	0.436	0.448	0.888

Table 4 VIF Results

Collinearity Statistics (VIF)

Outer VIF Values | Inner VIF Values

	VIF
OR5	3.356
PB1	2.151
PB2	2.144
PB3	2.114
PI1	2.406
PI2	2.682
PI3	2.517
PI4	2.427
PI5	2.394
PIN1	2.922
PIN2	2.900
PIN3	2.861
PR1	2.248
PR2	2.312
PR3	2.384

Collinearity Statistics (VIF)

Outer VIF Values | Inner VIF Values

	VIF
PI3	2.517
PI4	2.427
PI5	2.394
PIN1	2.922
PIN2	2.900
PIN3	2.861
PR1	2.248
PR2	2.312
PR3	2.384
TMS1	1.815
TMS2	1.836
TMS3	1.682
VS1	2.249
VS2	2.311
VS3	2.160

Collinearity Statistics (VIF)

Outer VIF Values | Inner VIF Values

	VIF
OR5	3.356
PB1	2.151
PB2	2.144
PB3	2.114
PI1	2.406
PI2	2.682
PI3	2.517
PI4	2.427
PI5	2.394
PIN1	2.922
PIN2	2.900
PIN3	2.861
PR1	2.248
PR2	2.312
PR3	2.384

Collinearity Statistics (VIF)

Outer VIF Values | Inner VIF Values

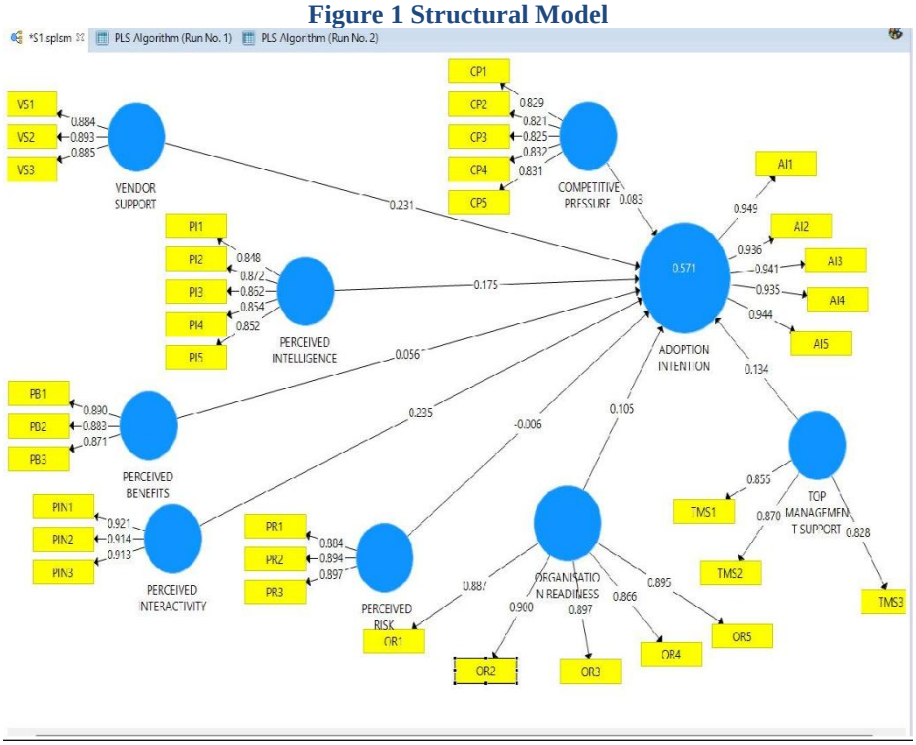
	VIF
AI1	6.501
AI2	5.269
AI3	5.637
AI4	5.188
AI5	5.992
CP1	2.114
CP2	2.084
CP3	2.103
CP4	2.052
CP5	2.145
OR1	3.069
OR2	3.425
OR3	3.220
OR4	2.685
OR5	3.356

Discriminant validity was assessed using the Fornell Larcker criterion. As shown in Table 4 & 5, the square root of the AVE for each construct was greater than its correlations with other constructs, confirming adequate discriminant validity (Fornell & Larcker, 1981). Collectively, these results demonstrate that the measurement model is both reliable and valid, providing a robust foundation for subsequent structural model analysis.

4.2.Structural Model

The measurement model was deemed reliable and valid, as indicated by the acceptable values of AVE, CR, and Cronbach's alpha. Discriminant validity (discriminant validity among the study's constructs is confirmed in Table 4 and 5) was also confirmed using the Fornell-Larcker criterion. Subsequently, the structural model was analyzed to evaluate the hypothesized relationships between the constructs using PLS-SEM.

Figure 1 Structural Model

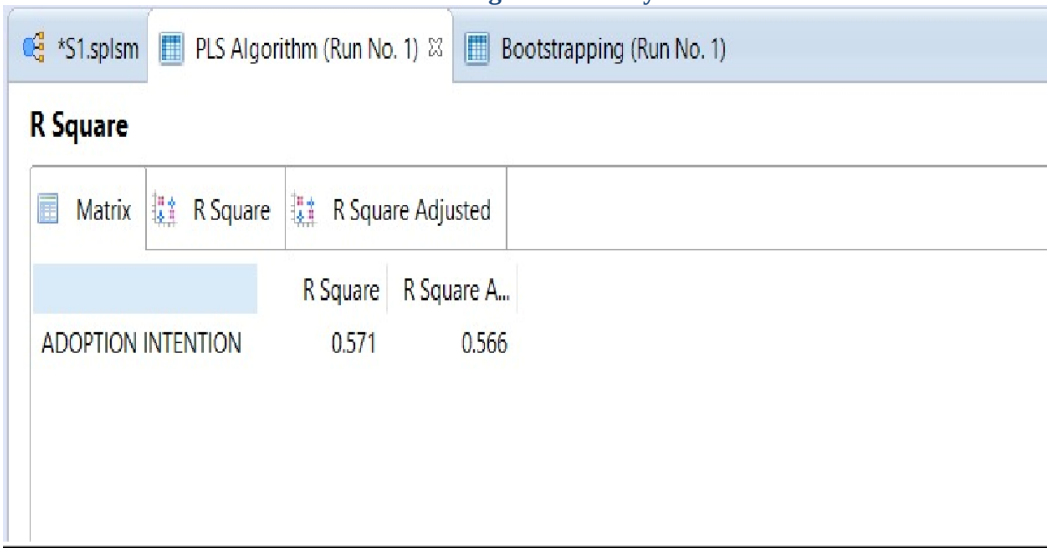


4.3. Structural Model Assessment

Prior to hypothesis testing, collinearity among predictor constructs was assessed using inner VIF values. All inner VIF values were below the conservative threshold of 3.3, indicating absence of multicollinearity concerns at the structural level.

The structural model explains 57.1% of the variance (R^2 = 0.571) in AI adoption intention, indicating moderate-to-substantial explanatory power in line with organizational technology adoption studies.

Table 5 Regression Analysis



Bootstrapping (5,000 resamples) was conducted to evaluate path significance. The results reveal that perceived interactivity ($\beta = 0.235$, $p < 0.001$) and vendor support ($\beta = 0.231$, $p < 0.001$) exert the strongest positive effects on AI adoption intention. Perceived intelligence ($\beta = 0.175$, $p < 0.001$) and top management support ($\beta = 0.134$, $p < 0.001$) also significantly influence adoption intention, though with comparatively smaller effect magnitudes. Additionally, organizational readiness ($\beta = 0.105$, $p = 0.003$) and competitive pressure ($\beta = 0.083$, $p = 0.014$) demonstrate statistically significant but modest effects.

Conversely, perceived benefits ($\beta = 0.056$, $p = 0.096$) and perceived risk ($\beta = 0.006$, $p = 0.857$) do not appear to influence adoption intention. The values for effect size (f) suggest that perceived interactivity and vendor support have the largest impact (increased incremental explanatory power) to the model, followed by organizational and environmental factors which have much smaller, though noticeable effects. The effect size for perceived risk was very small, further indicating a non-significant structural relationship.

The predictive relevance was measured using blindfolding; Q value > 0, thus adequate, and the blindfolded model can achieve some level of predictive relevance, which indicates that the proposed model is likely to have out-of-sample predictive power.

Model fit was measured using SRMR value. The model had an SRMR value < 0.08, suggesting an acceptable fit and overall adequacy of the model. All in all, it suggests that the specific AI-oriented technological factors and support factors within the system's ecosystem are a much greater predictor of an institutional adoption decision than the traditional perceived benefits and risks.

5.DISCUSSION

This study builds upon the Technology Organization Environment (TOE) framework, and its key contribution lies in its demonstration that the technological aspect of the framework necessitates a paradigm shift in its application to intelligent systems. Where conventional applications of the TOE framework typically focus on dimensions like relative advantage, compatibility, and complexity, this study's results indicate that such dimensions may no longer adequately capture the evaluation criteria by which organizations perceive and decide to adopt AI technologies. Instead, specific AI-oriented characteristics, namely perceived intelligence and perceived interactivity, were found to be critical determinants. This finding highlights a shift in organizational evaluation logic for intelligent systems, wherein the system's capacity to demonstrate human-like cognitive processes and dynamically engage with its users and environment are deemed paramount over conventional technology assessment factors.

One of the most significant findings of this study is the non-significant impact of perceived benefits and perceived risk. This finding challenges the pervasive benefit-risk paradigm that has long been a cornerstone of organizational technology adoption research. Contrary to the long-standing notion that perceived usefulness and risk drive organizational technology adoption decisions, higher education institutions have been found not to consider performance gains or the minimization of uncertainty as the primary factors in AI adoption decisions.

Rather, they prioritize how intelligently a system operates and interacts within the learning environment. This result signals a substantial shift in the way organizations conceptualize and evaluate emerging technologies.

The strong positive influence of perceived interactivity further supports the value placed on real-time, dynamic engagement in adopting AI technologies. Organizations are inclined to adopt systems that are responsive, interactive, and adaptive, reflecting a growing expectation for AI systems to support seamless and context-aware learning processes. Alongside perceived intelligence, these findings suggest that AI systems are increasingly viewed not as passive tools but as dynamic partners in the educational process. The insignificance of perceived benefits can be interpreted as an expectation that performance improvements are inherently part of the development of AI, and the lack of significance for perceived risk is indicative that organizations are

embracing AI as a necessary part of the future, rather than viewing it with trepidation. From an organizational perspective, this study also confirms that internal readiness and top management support play critical roles in facilitating AI adoption. Both organizational readiness and top management support had positive structural paths leading to AI adoption intention, illustrating that successful adoption hinges on the availability of an infrastructure conducive to technological adoption, institutional agreement, and strong executive endorsement. Top management support serves to legitimise AI initiatives, decrease the level of uncertainty associated with adoption and implement a coordination mechanism between the departments; whereas organisational readiness may reflect the practical feasibility that the institution can adapt an intelligent system to its operational context. All in all, it supports the view that both factors within the organisation can be viewed as prerequisites or drivers of successful adoption of intelligent systems. Finally, the study also underscores the importance of environmental factors, namely vendor support and competitive pressure. The highly significant effect of vendor support confirms the growing dependency of higher education on the IT ecosystem for system implementation, maintenance and upgrades; this extends the TOE framework in its contemplation of the importance of dynamic and relationships with third parties in the
adoption and implementation process. Although competitive pressure was significant, it appears to act as a trigger that amplifies existing adoption intentions or institutional preferences rather than a foundational driver. Competitive pressure helps maintain institutional competitiveness but does not, by itself, initiate a shift toward AI adoption. Taken as a whole, these findings enrich the literature by suggesting that the unique nature of intelligent systems requires a revised framework for assessing the technological capabilities and ecosystem support mechanisms that contribute to AI adoption in higher education contexts.

Theoretical Implications

First, this study contributes to the body of organizational technology adoption research by demonstrating that the evaluative process for intelligent systems differ significantly from that for conventional IT systems. Whereas most models of IT adoption rely on perceived usefulness and risk as major antecedents, this study shows that, at least in higher education, intention to adopt AI is more influenced by perceived intractability, perceived intelligence, and the supporting ecosystem than by these factors. This work challenges the prolonged dominance of benefit-risk logic in studies of intelligent technology and offers evidence for a shift toward cognitive-behavioral and other AI-specific dimensions. Second, this work extends the Technology-Organization-Environment (TOE) framework. Typically, the technological aspect of TOE focuses on technological characteristics such as relative advantage or complexity, rather than an institution's cognition and understanding of their implications. This study expands the framework by adding AI-specific cognition constructs to the technological domain, providing a basis for addressing more specific features and functions of new types of intelligent technologies rather than only the static qualities that have driven much of the IT research. Third, this study extends the literature on the adoption of AI in higher education. Where most studies on this topic use IT frameworks such as TAM or UTAUT to determine the extent of acceptance based on the users and individual experiences they reflect, this research uses an organizational-level analysis approach which highlights the significance of institutional readiness, top management support, vendor capabilities, and competition for its organizational integration. Thus, this study provides more holistic reasoning for why a specific organization would opt to integrate AI and opens the doors for other research to include a multi-level perspective of the technology adoption process.

Practical Implications

The results of this study provide direct advice for policymakers, university decision-makers, and AI technology vendors on how to approach AI integration, which differs greatly from traditional IT adoption strategy. Given that organisational readiness, top management support, and vendor relationships significantly affect adoption decisions for AI, a governmental focus on facilitating organisational transformation toward intelligent systems seems crucial. This approach could benefit from developing an AI Capability Maturity Model for higher education. The model will help identify institutional status and future directions for developing AI capabilities, likely including a stage for basic infrastructure development; for experimental AI pilot integration; for formal cross-organizational AI integration; and for an ideal phase of AI as a strategic driver. Linking funding to institutional progress across these stages will ensure coordinated, meaningful integration of intelligent systems rather than disjointed or short-sighted initiatives. Since perceived benefit and risk are insignificant factors in AI adoption in higher education, university leaders should not assume that greater benefits or reduced risk are sufficient motivators for successful AI adoption. Instead of focusing on adopting AI, an institution should consider conducting an AI Readiness Audit. The audit should include assessing key factors, such as infrastructure readiness, employees' digital literacy, the institution's data governance processes, leadership's commitment to support innovation, and dependence on the existing vendor, to determine the readiness of the organisation for AI adoption. An organizational commitment to proactive integration should be in the direction of strategic adoption based on readiness and potential, not reactive technology acquisition. The strong positive influence of perceived intractability on adoption intention suggests that users prefer interactive systems that offer more dynamic interaction, and that AI vendors should focus their design principles and marketing strategy on this feature. An ideal design should highlight interactivity through loops, context-awareness, and the transparency of the decision-making process. The marketing strategy should focus on the added value of such interactivity in pedagogical/organizational contexts rather than a transaction.

6.LIMITATIONS

The cross-sectional design of the study limits its ability to establish causal relationships; therefore, longitudinal studies would be beneficial for examining the dynamics of AI adoption intention and actual outcomes. The current study focused only on higher education institutions in one country, which limits the generalisability of the findings to institutions with different cultural and policy backgrounds. Therefore, a cross-country or comparative study is needed. The study focuses on organisations' decisions on AI adoption rather than individual-level factors such as teachers' and students' behaviour, which may interact with organisational decisions. A multi-level study should be considered to better integrate those dynamics. Additional variables such as algorithmic transparency, ethical considerations, and data management could also be explored beyond technological cognition as part of the technological perspective in the TOE framework to better understand the decision to adopt. Finally, this study examines only adoption intention and does not examine adoption and performance outcomes.

7.FUTURE RESEARCH DIRECTIONS

The limitations of this research suggest several research directions. Adding cross-country or multi-country research will provide a more comprehensive perspective on AI adoption. A longitudinal study would help explore the process of AI adoption over time. Incorporating individuals' perspectives into the current organisational-level study would enable a multi-level examination of how organisational and individual factors interact, supporting a more thorough investigation of the topic. The TOE framework's technology variable could be extended to include the cognitive complexity of new technology in the context of AI, such as algorithm transparency, ethical concerns, and data management, as part of the factors determining technology adoption decisions. It will also be valuable to bridge the gap between adoption intention and performance outcomes to explain the actual success of AI implementation in practice.

8.CONCLUSION

This research investigates the determinants of AI adoption in higher education institutions by adapting and extending the TOE framework. The results indicate that traditional benefits-risks considerations are not primary drivers of organisational decisions to adopt AI, whereas AI-specific technological capabilities, organisational readiness, leadership support, and overall support systems play a crucial role. Perceptions of interactability and intelligence are particularly important in shaping adoption intention, shifting the focus from standard IT evaluation to examining cognitive and dynamic system features. Incorporating AI-specific technological cognition into the technological component of TOE enables a deeper understanding of the unique technological considerations required for intelligent systems. The focus on the organizational level also underscores the importance of institutional readiness and strategic alignment in achieving effective integration of AI. Thus, AI adoption within higher education institutions must be seen not just as a technological issue but as a facet of a broader organizational transformation. Future research should also examine the dynamics of AI adoption at multiple levels and its impact on implementation to guide institutions through the changes of digital transformation

REFERENCES

1. Abed, S. S. (2020). Social commerce adoption using TOE framework: An empirical investigation of Saudi Arabian SMEs. International Journal of Information Management, 53, 102118. https://doi.org/10.1016/j.ijinfomgt.2020.102118
2. Akter, S., Michael, K., Uddin, M. R., McCarthy, G., & Rahman, M. (2022). Transforming business using digital innovations: The application of AI, blockchain, cloud, and data analytics. Annals of Operations Research, 308(1–2), 7–39. https://doi.org/10.1007/s10479-020-03620-w
3. Alam, M. G. R., Masum, A. K. M., Beh, L. S., & Hong, C. S. (2016). Critical factors influencing decision to adopt human resource information system (HRIS) in hospitals. PLoS ONE, 11(8), e0160366. https://doi.org/10.1371/journal.pone.0160366
4. Almaiah, M. A., Al-Khasawneh, A., & Althunibat, A. (2020). Exploring the critical challenges and factors influencing the adoption of e-learning systems during the COVID-19 pandemic. Education and Information Technologies, 25(6), 5261–5280. https://doi.org/10.1007/s10639-020-10219-y
5. Al-Maroof, R. S., Salloum, S. A., Hassanien, A. E., & Shaalan, K. (2023). Fear from COVID-19 and technology adoption: The impact of Google Meet during the Coronavirus pandemic. Interactive Learning Environments, 31(3), 1293–1308. https://doi.org/10.1080/10494820.2020.1830121
6. Alshamaila, Y., Papagiannidis, S., & Li, F. (2013). Cloud computing adoption by SMEs in the north east of England: A multi-perspective framework. Journal of Enterprise Information Management, 26(3), 250–275. https://doi.org/10.1108/17410391311325225 Amherst, S., & Tussyadiah, I. P. (n.d.). Travel and tourism research association: Advancing tourism research globally.
7. Arpaci, I. (2017). Antecedents and consequences of cloud computing adoption in education to achieve knowledge management. Computers in Human Behavior, 70, 382–390. https://doi.org/10.1016/j.chb.2017.01.024
8. Awa, H. O., & Ojiabo, O. U. (2016). A model of adoption determinants of ERP within organizations. Information Development, 32(4), 1133–1148. https://doi.org/10.1177/0266666915571422
9. Baker, J. (2012). The technology–organization–environment framework. In Y. K. Dwivedi, M. R. Wade, & S. L. Schneberger (Eds.), Information systems theory: Explaining and predicting our digital society (pp. 231–245). Springer.
10. Baker, R. S., & Inventado, P. S. (2014). Educational data mining and learning analytics. In J. A. Larusson & B. White (Eds.), Learning analytics (pp. 61–75).

Springer. https://doi.org/10.1007/978-1-4614-3305-7_4
12. Baker, T., & Smith, L. (2019). Educ-AI-tion rebooted? Exploring the future of artificial intelligence in schools and colleges. Nesta.
13. Bartneck, C., Kulić, D., Croft, E., & Zoghbi, S. (2009). Measurement instruments for anthropomorphism, animacy, likeability, perceived intelligence and safety of robots. International Journal of Social Robotics, 1(1), 71–81.
14. Basloom, R. S., Sani Mohamad, M. H., & Auzair, S. M. (2022). Applicability of public sector reform initiatives of the Yemeni government from the integrated TOE-DOI framework. International Journal of Innovation Studies, 6(4), 286–302.
15. Basloom, M. M., Alshammari, S. H., & Alqahtani, S. M. (2022). Adoption of digital technologies in higher education institutions: A TOE framework perspective. Education and Information Technologies, 27(6), 7925–7945.
16. Battisti, G., Hollenstein, H., Stoneman, P., & Woerter, M. (2007). Inter- and intra-firm diffusion of ICT in the United Kingdom and Switzerland. Economics of Innovation and New Technology, 16(8), 669–687.
17. Bond, M., Marín, V. I., Dolch, C., Bedenlier, S., & Zawacki-Richter, O. (2023). Artificial intelligence in higher education: A systematic literature review. Computers and Education: Artificial Intelligence, 4, 100087.
18. Brynjolfsson, E., & McAfee, A. (2017). Machine, platform, crowd: Harnessing our digital future. W. W. Norton.
19. Buchanan, T., Sainter, P., & Saunders, G. (2013). Factors affecting faculty use of learning technologies. Journal of Computing in Higher Education, 25(1), 1–11.
20. Carrillo, C., & Flores, M. A. (2020). COVID-19 and teacher education: A literature review of online teaching and learning practices. European Journal of Teacher Education, 43(4), 466–487.
21. Chan, C. K. Y. (2023). A comprehensive AI policy education framework for university teaching and learning. Educational Technology Research and Development, 71, 163–179.
22. Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI. Computers and Education: Artificial Intelligence, 4, 100116.
23. Chassignol, M., Khoroshavin, A., Klimova, A., & Bilyatdinova, A. (2018). Artificial intelligence trends in education. Procedia Computer Science, 136, 16–24.
24. Chatterjee, S., & Bhattacharjee, K. (2020). Adoption of artificial intelligence in higher education. Technological Forecasting and Social Change, 160, 120220.
25. Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. IEEE Access, 8, 75264–75278.
26. Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. International Journal of Educational Technology in Higher Education, 20(1), 22.
27. Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. Harvard Business Review, 96(1), 108–116.
28. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340.
29. Dempere, J., Modugu, K., Hesham, A., & Ramasamy, L. K. (2023). The impact of ChatGPT on higher education. Education and Information Technologies.
30. Depietro, R., Wiarda, E., & Fleischer, M. (1990). The context for change: Organization, technology, and environment. In The processes of technological innovation (pp. 151–175). Lexington Books.
31. Dhawan, S. (2020). Online learning: A panacea in the time of COVID-19 crisis. Journal of Educational Technology Systems, 49(1), 5–22.
32. Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of big data. International Journal of Information Management, 48, 63–71.
33. Dwivedi, Y. K., et al. (2021). Artificial intelligence: Multidisciplinary perspectives. International Journal of Information Management, 57, 101994.
34. Eager, B., & Brunton, R. (2023). Prompt engineering and generative AI in education. Journal of Educational Technology Systems, 52(1), 45–59.
35. Farrelly, T., & Baker, N. (2023). Generative AI and academic integrity. Assessment & Evaluation in Higher Education.
36. Holmes, W., Bialik, M., & Fadel, C. (2019). Artificial intelligence in education. Center for Curriculum Redesign.
37. Holmes, W., Bialik, M., & Fadel, C. (2022). Artificial intelligence in education: Promise and implications for teaching and learning (2nd ed.). Center for Curriculum Redesign.
38. Hu, X., Gong, Y., Lai, C., & Leung, F. (2020). The relationship between teachers' pedagogical beliefs and technology integration. Educational Technology Research and Development.
39. Hwang, G. J., & Tu, Y. F. (2021). Roles and research trends of artificial intelligence in mathematics education. Mathematics, 9(6), 584. https://doi.org/10.3390/math9060584
40. Jääskelä, P., Häkkinen, P., & Rasku-Puttonen, H. (2017). Teacher beliefs regarding learning and technology. Teaching in Higher Education, 22(4), 425–438.
41. Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand. Business Horizons, 62(1), 15–25.
42. Luckin, R., et al. (2016). Intelligence unleashed. Pearson.
43. Luckin, R., et al. (2017). Artificial intelligence and the future of learning. UCL Institute of Education Press.
44. Masood, T., & Egger, J. (2019). Adopting augmented reality in manufacturing. Computers in Industry, 108, 100–111.
45. Ministry of Education. (2020). National education policy 2020. Government of India.
46. Mittal, P., Kaur, A., & Gupta, V. (2021). Artificial intelligence adoption in education. International

Journal of Educational Technology in Higher Education.

48. Ng, P. M. L., Lit, K. K., & Cheung, C. T. Y. (2022). Remote work as a new normal? Technology in Society, 70, 101982.
49. Ouyang, F., & Jiao, P. (2021). Artificial intelligence in education: The three paradigms. Computers and Education: Artificial Intelligence, 2, 100020.
50. Pillai, R., & Sivathanu, B. (2020). Adoption of artificial intelligence-based chatbots in education. International Journal of Educational Technology in Higher Education.
51. Roll, I., & Wylie, R. (2016). Evolution and revolution in artificial intelligence in education. International Journal of Artificial Intelligence in Education, 26, 582–599.
52. Russell, S., & Norvig, P. (2021). Artificial intelligence: A modern approach (4th ed.). Pearson.
53. Selwyn, N. (2019). Should robots replace teachers? AI and the future of education. Polity Press.
54. Siemens, G., & Baker, R. S. (2012). Learning analytics and educational data mining. In Proceedings of the 2nd International Conference on Learning Analytics and Knowledge (pp. 252–254). https://doi.org/10.1145/2330601.2330661
55. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology. MIS Quarterly, 27(3), 425–478.
56. Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology. MIS Quarterly, 36(1), 157–178.
57. Winkler, R., & Söllner, M. (2018). Unleashing the potential of chatbots in education. In AMCIS Proceedings.
58. Woolf, B. P. (2010). Building intelligent interactive tutors. Morgan Kaufmann.
59. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Artificial intelligence applications in higher education. International Journal of Educational Technology in Higher Education, 16, 39.
60. Zawacki-Richter, O., Bond, M., Marín, V., & Gouverneur, F. (2020). Systematic review of research on artificial intelligence applications in higher education. International Journal of Educational Technology in Higher Education.
61. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2021). Artificial intelligence and higher education: Mapping research trends. International Journal of Educational Technology in Higher Education.
62. Zhai, X., Chu, X., Chai, C. S., et al. (2021). Artificial intelligence in education: A review from 2010 to 2020.