

The Role of Artificial Intelligence in Shaping Students' Sustainable Education and Career Development: An Extended Technology–Organization–Environment (TOE) Perspective

Dr. Preeti Kulkarni¹; Ms.Vaishnavi Kulkarni²; Dr. Niraj Chaudhari³; Ms.Gautami Upadhyay⁴

¹Director, Dr. Moonje Institute of Management and Computer Studies, Nashik Email Id: preetimaheshk@gmail.com Orcid Id: 0009-0002-4080-1817

²Management Trainee, Prosperdream Detailing Services LLP Orcid Id: 0009-0006-1839-7335

³Associate Professor, Dr. Moonje Institute of Management and Computer Studies, Nashik, Orcid Id: 0000-0001-9167-9159

⁴Assistant Professor, Dr. Moonje Institute of Management and Computer Studies, Nashik, Orcid Id: 0009-0001-8441-7131

Abstract

The central purpose of education is to ensure the holistic development of learners, and delivering quality teaching and effective learning practices enables Higher Educational Institutions (HEIs) to attain long-term, meaningful learning outcomes; in today's academic context, both Artificial Intelligence (AI) and outcome-based education are receiving considerable scholarly attention, and this study examines how students perceive AI and the extent to which it influences sustainable learning and future career advancement. The research framework is grounded in the Technology–Organization–Environment (TOE) model, extended to incorporate social, educational, and career-related dimensions relevant to student populations; data were collected from 239 higher education students across multiple academic programs using a structured questionnaire developed in consultation with specialists in AI and sustainable education, and the measurement and structural models were validated using Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS, with descriptive analysis performed in IBM SPSS 23.0. The findings show that three core antecedents—social factors, technological factors, and organizational factors—significantly shape students' attitude toward AI, and attitude, in turn, positively influences students' perception of sustainable education and their career development, with all twelve hypothesized paths statistically supported ($p < 0.05$) and the model demonstrating acceptable reliability, validity, and predictive relevance ($Q^2 > 0.35$ across endogenous constructs). The study extends the classical TOE framework beyond its organizational-adoption origins into an individual-level, student-centred model of AI acceptance, linking technology adoption theory directly to sustainable-education and employability outcomes, and the findings offer empirically grounded guidance for HEIs seeking to integrate AI responsibly into curricula and student-support services.

Keywords: Artificial Intelligence; Sustainable Learning; Student Attitudes; Career Development; Higher Education; Technology–Organization–Environment (TOE) Framework; PLS-SEM.

1. Introduction

The role of Artificial Intelligence (AI) in the education sector has grown considerably in recent years. Computer- and machine-based teaching approaches are influencing learning outcomes significantly; in particular, AI-based pedagogical design and instructional tools are enabling both instructors and learners to achieve desired educational outcomes more effectively.

The present study examines the impact of AI on sustainable education and career development among students.

To this end, the study adopts the well-established Technology–Organization–Environment (TOE) framework and analyses data collected from 239 respondents using PLS-SEM.

AI is recognized as a technological innovation capable of addressing critical challenges in education while offering sustainable pathways for transformational learning. Within the Indian higher-education system in particular, the overall student experience and instructional process are undergoing transformation as a result of rapid technological advancement (Shalini & Tewari, 2020).

AI also assists teachers in predicting students' potential and in mitigating student dropout (Sarkar, 2018), and contemporary pedagogy increasingly emphasizes experiential learning.

Effective and sustainable learning increasingly depends on the purposeful integration of educational technology and AI into the learning process (Verma, 2018).

Attitude is widely regarded as the most determinative factor shaping how learners engage with new technology, and the present study evaluates three principal antecedents of that attitude—technological, organizational, and environmental/social factors.

The classical tripartite structure of attitude—cognitive, affective, and behavioural—maps onto the learning process: learners first register instructional inputs according to their individual learning style (cognitive); these inputs then shape learner engagement positively or negatively (affective); and sustainable, transformational learning is ultimately observed as a change in behaviour that supports career development (behavioural).

AI-enabled tools interact with learners' preferred modalities—visual, auditory, kinaesthetic, and audio-digital—thereby supporting more effective and sustainable learning across academic domains. Accordingly, this study evaluates the impact of AI on sustainable learning and career development using the TOE framework as its guiding theoretical lens.

2. Literature Review And Hypotheses Development

2.1. Theoretical Background

The learning environment has changed markedly with the emergence of innovative AI technologies. The extension of classroom teaching through virtual AI tools has facilitated not only instructional delivery and course design but has also contributed to more sustainable models of education (Ahmad, 2020).

In contemporary educational settings, AI adoption has made educational tasks more efficient and has enhanced the practicality of learning. Educators increasingly function as a bridge between AI capability and desired learning outcomes (Tuomi & Ilkka, 2018).

AI has a demonstrably positive impact on both academic delivery and administrative tasks: on one hand, it helps teachers provide more effective instructional support; on the other, it obliges teachers to take responsibility for decisions informed by data whose underlying logic may not always be fully explainable (Van der Vorst et al., 2019).

Students' attitudes toward AI implementation are shaped by multiple interacting factors. This study adopts the TOE framework, a well-validated multi-faceted theory capable of capturing technological vulnerabilities both within and outside an organization (Tornatzky & Fleischer, 1990), and applies it to explain variation in students' attitudes toward AI and their subsequent sustainable career growth.

Within this framework, organizational decisions to adopt an innovative technology are shaped jointly by environmental/social factors and organizational factors. Advanced technology entails cost, and the relative benefit that a technology confers is a key determinant of adoption (AlSheibani et al., 2018).

Technological factors capture the innovations available either inside the institution or across the wider sector; organizational factors capture strategic investment, top-management commitment, and institutional scale; and environmental factors capture market conditions, sector structure, and the roles of internal and external stakeholders (Tornatzky & Fleischer, 1990).

Empirical evidence supports the relevance of AI-related attitudes in educational contexts.

Pinto Dos Santos et al. (2018), examining medical students' attitudes toward AI, reported that a majority of respondents (77%) agreed that medical training requires an AI-enabled curriculum, reflecting a generally favourable and forward-looking learning attitude oriented toward practical, outcome-driven skill development.

Conversely, Bochniarz et al. (2021), studying 659 school students, found that a substantial proportion expressed distrust toward AI and perceived it as impersonal and inadequately governed—evidence that attitudes toward AI in education are not uniformly positive and are contingent on context, exposure, and institutional support.

2.2. Technological Factors

Technological factors describe both the degree of innovation available to an institution and its capacity to adopt cost-effective solutions, encompassing considerations of affordability and implementation effectiveness (Tornatzky & Fleischer, 1990).

For educational institutions, investment in technology-enhanced tools directly affects the quality of teaching and contributes to sustainable student career development (Collins et al., 1988).

As external technological expectations rise, institutions face growing pressure to enhance their capabilities; incremental technological change generally entails lower risk and cost than radical change (Hage, 2008; Tushman & Nadler, 1986).

The perceived relative advantage of adopting AI is a key determinant of adoption intensity (Zahi, 2010), and prior research consistently links relative advantage to the acceptance of new technologies (Aboelmaged, 2014; Kumar et al., 2016; Hung, 2016; Ifinedo, 2005; Zhai, 2015; Yang, 2015).

H1. Technological factors have a significant positive influence on students' attitude toward AI.

H2. Relative advantage significantly influences technological factors.

H3. Technology cost significantly influences technological factors.

2.3. Organizational Factors

Internal organizational attributes—structure, size, and available resources—play a decisive role in determining the success of new-technology adoption (Aboelmaged, 2014).

Departmental readiness, shaped by available resources and accessibility, influences whether AI implementation succeeds (Iacovou et al., 1995), and top-management commitment is critical: without leadership support, motivation, and vision, technological adoption is difficult to sustain (Ifinedo, 2005).

Prior studies confirm that leadership engagement is significantly associated with the success of innovation adoption (Hung et al., 2014; Zahi, 2010; Yang et al., 2015).

In educational institutions specifically, organizational factors additionally include faculty strength, student population, curriculum design, and institutional policy, while teachers' knowledge, technical skill, and trust in AI-enabled education further shape the pace of adoption.

H4. Organizational factors have a significant positive influence on students' attitude toward AI.

H5. Top-management support significantly influences organizational factors.

H6. Departmental readiness significantly influences organizational factors.

2.4. Environmental and Social Factors

Institutions shape their strategies and operations in response to the dynamics of the external environment (AlSheibani et al., 2018).

Two broad categories of factors influence the adoption of an innovation such as AI: internal factors, relating to institutional culture and climate, and external factors, including competitive pressure, market scope, and supplier or partner ecosystems (Ifinedo, 2005); together these define the broader context within which an institution operates (Chau & Tam, 1997).

In education specifically, successful AI adoption depends heavily on teachers' expertise, willingness to learn, attitude toward technological change, and pedagogical approach, while external drivers such as regulation, sector competition, and market uncertainty further encourage institutions to adopt innovative solutions (Kamath & Liker, 1994; Mansfield, 1968; Mansfield et al., 1977).

Within the present model, social factors are operationalized through students' knowledge of AI and their trust in AI-enabled systems.

H7. Social factors have a significant positive influence on students' attitude toward AI.

H8. Knowledge of AI significantly influences social factors.

H9. Trust in AI significantly influences social factors.

2.5. Attitude, Sustainable Education, and Career Development

Students' response patterns indicate that AI positively influences educational outcomes, particularly with respect to student progress and performance, faculty–student interaction, and classroom engagement and participation.

These findings reinforce the view that AI can enhance the quality of learning by fostering interactive, innovative, and supportive educational environments; as Kairu (2020) notes, AI adoption is associated with improved student progress and engagement.

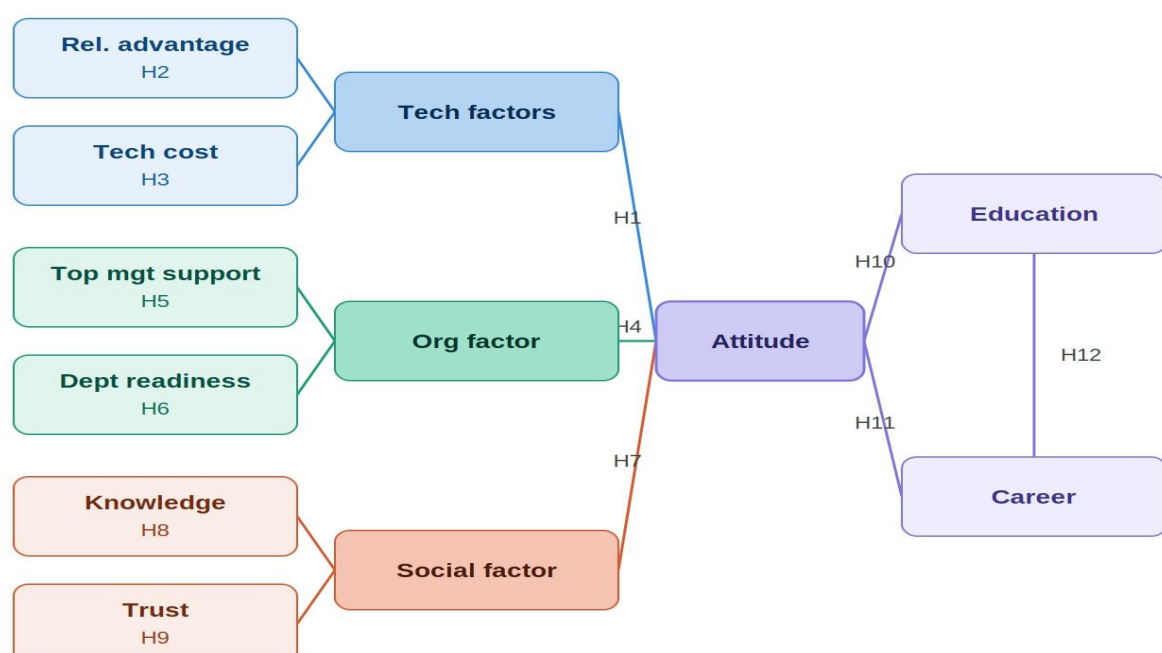
A favourable attitude toward AI is therefore expected to translate into stronger perceptions of sustainable education, which in turn should support students' career development.

H10. Students' attitude toward AI significantly influences their perception of sustainable education.

H11. Students' attitude toward AI significantly influences their career development.

H12. Students' perception of sustainable education significantly influences their career development.

Extended TOE structural model – hypothesized paths (H1–H12)



3. Research Methodology

3.1. Research Questions and Objectives

- RQ1: What is the current awareness level of students toward Artificial Intelligence (AI)?
- RQ2: What is the attitude of students toward Artificial Intelligence (AI)?
- RQ3: Which factors influence the use of AI, and how do they affect students' education and career growth?

The primary objective of the study is to evaluate the attitudes of students from different academic programs toward AI and to identify the key factors influencing their awareness, acceptance, and application of AI in education and career development.

3.2. Research Design and Sampling

The study follows a descriptive, cross-sectional research design and employed a non-probability judgmental sampling technique. Of 250 targeted participants, 239 valid responses were retained for analysis after data screening (95.6% usable response rate).

Data were collected using a structured questionnaire administered through both Google Forms and paper-based copies, developed in consultation with subject-matter specialists in AI and sustainable education to establish content validity.

3.3. Measurement and Analytical Technique

Prior technology-adoption research has relied on established models such as the Technology Acceptance Model (TAM) and the Technology–Organization–Environment (TOE) framework.

For this study, the TOE model (Baker, 2011) was selected as the most suitable theoretical lens and was extended by the authors to incorporate social, educational, and career-related dimensions relevant to student-level AI acceptance.

All constructs were measured using multi-item reflective scales. Descriptive statistics and demographic profiling were computed using IBM SPSS 23.0, and the measurement and structural models were estimated using Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS, a technique well suited to exploratory, theory-extension research with composite constructs and moderate sample sizes.

4. Data Analysis And Results

4.1. Awareness of AI-Enabled Features

Table 1. Mean rank analysis of perceived AI features in smart devices

AI-enabled feature	Mean	Rank
Social media	4.36	1
Search engines (e.g., Google)	4.21	2
Google Maps / GPS	4.19	3
Google keyboard	4.15	4
Online banking features	4.15	4
Chatbots	4.14	6
Online shopping app recommendations	4.14	6
Image/text recognition (e.g., Google Lens)	4.12	8
Search recommendations	4.11	9
Cameras	4.10	10
Streaming recommendations (Netflix, Prime Video)	4.08	11
Voice assistants	4.06	12
Auto-correction	4.05	13
Voice typing	4.05	13
Facial recognition	4.05	13

N = 239. Items rated on a 5-point scale; higher means indicate greater perceived presence/awareness of the AI feature.

Social media ranked first among the fifteen AI-enabled features assessed ($M = 4.36$), followed closely by search engines ($M = 4.21$) and location-based services ($M = 4.19$), indicating that students' AI awareness is anchored primarily in everyday consumer applications rather than formal educational tools.

4.2. Measurement Model Assessment

Following Hair et al. (2017), the measurement model was evaluated for indicator reliability, internal consistency reliability, convergent validity, and discriminant validity before the structural model was tested.

Table 2. Construct reliability and validity

Construct	Cronbach's alpha	rho_A	Composite reliability	AVE
Attitude	0.867	0.868	0.909	0.715
Career	0.882	0.883	0.919	0.739
Departmental Readiness	0.893	0.894	0.926	0.757
Education (sustainable learning)	0.871	0.871	0.912	0.721
Knowledge	0.814	0.821	0.890	0.730
Organizational Factor	—	1.000	—	—
Relative Advantage	0.880	0.881	0.912	0.676
Social Factor	0.890	0.894	0.914	0.605
Technology Cost	0.801	0.801	0.883	0.715
Technology Factors	—	1.000	—	—
Top Management Support	0.842	0.843	0.905	0.760
Trust	0.862	0.865	0.906	0.708

All indicator outer loadings exceeded the recommended 0.708 threshold (Hair et al., 2017); all AVE values exceeded 0.50 and composite reliability values exceeded 0.70 (Sarstedt, Ringle, & Hair, 2017), confirming convergent validity and internal consistency reliability.

Table 3. Discriminant validity – Heterotrait–Monotrait (HTMT) ratio

	Attitude	Career	Dept. Readiness	Education	Knowledge	Rel. Advantage	Social Factor	Tech Cost	Top Mgt	Trust
Career	0.801									
Dept. Readiness	0.740	0.599								
Education	0.803	0.852	0.613							
Knowledge	0.743	0.670	0.721	0.735						
Rel. Advantage	0.859	0.712	0.700	0.786	0.743					
Social Factor	0.820	0.658	0.754	0.745	0.076	0.844				
Tech Cost	0.776	0.660	0.588	0.760	0.799	0.889	0.858			
Top Mgt	0.789	0.648	0.872	0.769	0.757	0.762	0.791	0.736		
Trust	0.797	0.585	0.705	0.679	0.809	0.836	0.831	0.818	0.739	

All HTMT values fall below the conservative 0.90 threshold (Kline, 2010), and all variance inflation factor (VIF) values are below 3.3, jointly indicating that discriminant validity is established and multicollinearity is not a concern.

4.3. Structural Model Assessment

Table 4. Coefficient of determination (R^2)

Endogenous construct	R^2	R^2 adjusted
Attitude	0.658	0.653
Career	0.726	0.723
Education	0.490	0.487
Organizational Factor	0.998	0.998
Social Factor	1.000	1.000
Technology Factors	0.999	0.999

Table 5. Hypothesis testing results (structural path estimates)

Hyp.	Path	β (O)	Mean (M)	SD	t-statistic	p-value	Decision
H1	Technology Factors → Attitude	0.419	0.425	0.082	5.110	0.000	Supported
H2	Relative Advantage → Technology Factors	0.793	0.786	0.092	8.586	0.000	Supported
H3	Technology Cost → Technology Factors	0.257	0.260	0.104	2.465	0.014	Supported
H4	Organizational Factor → Attitude	0.284	0.293	0.077	3.694	0.000	Supported
H5	Top Management → Organizational Factor	0.601	0.593	0.125	4.823	0.000	Supported
H6	Departmental Readiness → Organizational Factor	0.464	0.466	0.127	3.654	0.000	Supported
H7	Social Factor → Attitude	0.189	0.180	0.078	2.421	0.016	Supported
H8	Knowledge → Social Factor	0.455	0.454	0.016	28.181	0.000	Supported
H9	Trust → Social Factor	0.632	0.632	0.019	32.927	0.000	Supported
H10	Attitude → Education	0.700	0.703	0.042	16.580	0.000	Supported
H11	Attitude → Career	0.231	0.237	0.060	3.825	0.000	Supported
H12	Education → Career	0.674	0.670	0.055	12.259	0.000	Supported

Bootstrapping performed with 5,000 resamples. All twelve hypothesized paths are statistically significant at $p < 0.05$, supporting the extended TOE model.

Table 6. Predictive relevance (Q^2) via blindfolding

Construct	SSO	SSE	$Q^2 (= 1 - SSE/SSO)$
Attitude	956.000	519.314	0.457
Career	956.000	449.362	0.530
Education	956.000	622.842	0.348
Organizational Factor	1673.000	570.742	0.659
Social Factor	1673.000	669.877	0.600
Technology Factors	1912.000	764.716	0.600

Q^2 values exceed the 0.35 threshold associated with strong predictive relevance (Hair et al., 2017) for all reported endogenous constructs.

Table 7. Model fit summary

Fit index	Saturated model	Estimated model
SRMR	0.070	0.081
d_ULS	7.793	10.506

SRMR values below the 0.08–0.10 guideline threshold indicate acceptable model fit (Henseler, Ringle, & Sarstedt, 2015).

4.4. Respondent Profile

Of the 239 respondents, 60.7% were aged 18–21 years, 32.6% were aged 22–26 years, and 1.6% were above 26 years. In terms of academic level, 47.3% were undergraduate students, 38.5% postgraduate, 6.7% doctoral scholars, 5.0% diploma/pre-university students, and 2.5% enrolled in professional courses.

By discipline, 65.3% were from arts and science, 27.6% from engineering, 4.2% from professional studies, 2.1% from medicine, and the remainder from law.

Regarding device ownership, 44.4% owned two smart devices, 30.5% owned one, 15.1% owned three, and a smaller proportion owned more than three.

In terms of daily usage, 76.6% used smart devices for 1–8 hours, 19.7% for 9–16 hours, and a small remainder for 17–24 hours. Awareness of AI was most commonly attributed to the internet (55.6%), followed by social media (33.1%), newspapers (6.3%), and magazines or advertisements.

Device platform usage was dominated by Android (94.6%) over iOS (5.4%). Self-reported AI awareness was distributed as follows: 34.3% highly aware, 31.4% aware, 26.4% neutral, 6.3% low awareness, and a small remainder unaware.

5. Discussion

A foremost requirement of the current digital era is to recognize the potential risks associated with the unconscious or uncontrolled use of AI. Because AI remains a comparatively new and rapidly evolving technology, its full implications are not yet widely understood.

It is therefore important for educational institutions to introduce dedicated AI-related coursework or structured programs that build awareness at an early stage of academic life.

Smartphone users, more broadly, would similarly benefit from education not only about device features but also about how AI-driven applications shape everyday decision-making; a considerable proportion of users remain unaware of the extent to which AI subtly influences their choices and behaviours.

The demographic and behavioural profile of respondents indicates that AI awareness is concentrated among younger, undergraduate, Android-using students who primarily encounter AI through consumer applications such as social media and search engines rather than through structured academic exposure.

The extended TOE framework applied in this study performed well empirically: technological, organizational, and social factors each exerted a significant positive influence on attitude, and attitude in turn significantly predicted both perceived sustainable-education outcomes and career development, with acceptable predictive relevance ($Q^2 > 0.35$) across the model's endogenous constructs.

This supports the generalizability of the extended model for future research on AI awareness and adoption in other educational and cultural contexts.

Overall, the findings reaffirm that AI is among the most consequential drivers of contemporary technological transformation in higher education.

While a segment of students demonstrates strong familiarity with AI applications, a substantial proportion still lacks sufficient understanding of its underlying mechanisms and implications.

This underscores the need for institutions to invest in awareness-building, targeted training, and the responsible integration of AI so that its benefits for learning and career development can be more equitably realized.

6. Theoretical And Practical Implications

6.1. Theoretical Implications

This study contributes to the technology-adoption literature by extending the Technology–Organization–Environment (TOE) framework—originally developed to explain firm-level innovation adoption—to an individual, student-centred context.

By incorporating social, educational, and career-related constructs, the study demonstrates that the TOE logic can meaningfully explain attitude formation and behavioural outcomes at the level of the individual learner, offering a template for future research linking technology-adoption theory to sustainability and employability outcomes in education.

6.2. Practical Implications

- HEIs should embed structured AI literacy modules within curricula rather than relying on incidental, consumer-driven exposure to AI.
- Institutional leadership (top management) and departmental readiness are both significant levers for improving organizational conditions for AI adoption; investment should target both dimensions jointly.
- Building student trust and knowledge should be prioritized as the strongest levers of favourable social factors, which in turn shape overall attitude toward AI.
- Because attitude strongly predicts perceived sustainable-education outcomes and career development, student-facing AI initiatives should be framed explicitly around employability and long-term learning value, not solely technical competence.

7. Limitations And Future Research

The study is subject to several limitations that should be considered when interpreting its findings.

First, the non-probability judgmental sampling technique and the geographically concentrated sample limit the generalizability of results to other institutional or national contexts.

Second, the cross-sectional design captures attitudes at a single point in time and cannot establish causal or longitudinal relationships among constructs.

Third, data were collected via self-report, which may be subject to common-method bias, although the discriminant-validity and VIF diagnostics reported here mitigate this concern.

Future research should employ probability-based, cross-institutional, and cross-national samples; adopt longitudinal or experimental designs to establish causality; and consider moderating variables such as discipline, prior AI exposure, and institutional AI policy to refine the extended TOE model proposed here.

8. Conclusion

Amid the rapid transformation of technological domains, Artificial Intelligence has emerged as a key driver of innovation in higher education.

While a portion of students is already familiar with AI applications, a substantial segment of the student population still lacks adequate awareness of its capabilities and implications.

It is therefore essential for institutions to disseminate structured knowledge about AI and to provide training on its effective and responsible use.

This study set out to examine students' awareness of AI and its impact on sustainable education and career development using an extended TOE framework; the results confirm that technological, organizational, and social factors jointly shape students' attitude toward AI, and that this attitude meaningfully supports both sustainable learning outcomes and career development.

These findings offer empirically grounded guidance for HEIs seeking to integrate AI responsibly and effectively into the student learning experience.

References

- Aboelmaged, M. G. (2014). Predicting e-readiness at firm-level: An analysis of technological, organizational and environmental (TOE) effects on e-maintenance readiness in manufacturing firms. *International Journal of Information Management*, 34(5), 639–651.
- AlSheibani, S., Cheung, Y., & Messom, C. (2018). Artificial Intelligence adoption: AI-readiness at firm-level. *Proceedings of the Pacific Asia Conference on Information Systems (PACIS)*.

Baker, J. (2011). The technology–organization–environment framework. In Y. K. Dwivedi, M. R. Wade, & S. L. Schneberger (Eds.), *Information Systems Theory* (pp. 231–245). Springer.

Bochniarz, K. T., et al. (2021). Attitudes toward artificial intelligence among school students. [Journal details to be completed by the author(s)].

Chan, C. K. Y. (2023). A comprehensive AI policy education framework for university teaching and learning. *International Journal of Educational Technology in Higher Education*, 20, Article 38.

Chau, P. Y. K., & Tam, K. Y. (1997). Factors affecting the adoption of open systems: An exploratory study. *MIS Quarterly*, 21(1), 1–24.

Collins, P. D., Hage, J., & Hull, F. M. (1988). Organizational and technological predictors of change in automaticity. *Academy of Management Journal*, 31(3), 512–543.

Demir, K. (2025). Will AI become a threat to higher education sustainability? A study of students' views. *Sustainability*, 16(11), Article 4596.

Environmental Sciences Europe. (2025). Using artificial intelligence in sustainability teaching and learning. *Environmental Sciences Europe*, 37.

Farooq, U., Malik, S. A., & Syed, A. S. (2024). Revolutionizing higher education: The transformative impact of artificial intelligence on teaching, learning, and career preparation. *ShodhKosh: Journal of Visual and Performing Arts*, 5(1).

Garbowski, M., Kozitska, N., Poliakova, Y., Kornilova, N., & Synytsia, L. (2024). Artificial Intelligence's (AI) role in higher education: Challenges and applications. *Academy of Marketing Studies Journal*, 28(4), 1–9.

Hage, J. (2008). Organizational innovation and organizational change. *Annual Review of Sociology*, 25(1), 597–622.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). Sage.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135.

Hung, S.-Y., Hung, W.-H., Tsai, C.-A., & Jiang, S.-C. (2014). Critical factors of hospital adoption on CRM system: Organizational and information system perspectives. *Decision Support Systems*, 48(4), 592–603.

Iacovou, C. L., Benbasat, I., & Dexter, A. S. (1995). Electronic data interchange and small organizations: Adoption and impact of technology. *MIS Quarterly*, 19(4), 465–485.

Ifinedo, P. (2005). Measuring Nigeria's e-Government maturity: Fitting theory to reality. *Electronic Government, an International Journal*, 2(4), 386–406.

Kairu, C. (2020). Artificial intelligence and student progress: Emerging evidence from higher education. [Journal details to be completed by the author(s)].

Kamath, R. R., & Liker, J. K. (1994). A second look at Japanese product development. *Harvard Business Review*, 72(6), 154–170.

Katsamakas, E., Pavlov, O. V., & Saklad, R. (2024). Artificial intelligence and the transformation of higher education institutions. *arXiv preprint*.

Kline, R. B. (2010). *Principles and practice of structural equation modeling* (3rd ed.). Guilford Press.

Mansfield, E. (1968). *Industrial research and technological innovation: An econometric analysis*. Norton.

Mansfield, E., Rapoport, J., Romeo, A., Wagner, S., & Beardsley, G. (1977). Social and private rates of return from industrial innovations. *Quarterly Journal of Economics*, 91(2), 221–240.

"New era of artificial intelligence in education: Towards a sustainable multifaceted revolution." (2023). *Sustainability*, 15, Article 12451.

Owoc, M. L., Sawicka, A., & Weichbroth, P. (2021). Artificial intelligence technologies in education: Benefits, challenges and strategies of implementation. *arXiv preprint*.

Pinto Dos Santos, D., et al. (2018). Medical students' attitude towards artificial intelligence: A multicentre survey. *European Radiology*, 29, 1640–1646.

Portocarrero Ramos, H. C., Cruz Caro, O., Sánchez Bardales, E., Quiñones Huatangari, L., Campos Trigos, J. A., & Maicelo Guevara, J. L. (2025). Artificial intelligence skills and their impact on the employability of university graduates. *Frontiers in Artificial Intelligence*, 8.

Sajja, R., Sermet, Y., Cikmaz, M., Cwiertny, D., & Demir, I. (2023). Artificial intelligence-enabled intelligent assistant for personalized and adaptive learning in higher education. *arXiv preprint*.

Sarkar, S. (2018). AI could help identify students who need extra attention. [Journal details to be completed by the author(s)].

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2017). Partial least squares structural equation modeling. In C. Homburg, M. Klarmann, & A. Vomberg (Eds.), *Handbook of Market Research* (pp. 1–40). Springer.

Shalini, & Tewari, R. (2020). Technological transformation in Indian education: Opportunities and challenges. [Journal details to be completed by the author(s)].

Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation*. Lexington Books.

Tushman, M. L., & Nadler, D. A. (1986). Organizing for innovation. *California Management Review*, 28(3), 74–92.

Tuomi, I. (2018). The impact of artificial intelligence on learning, teaching, and education: Policies for the future. Publications Office of the European Union.

Van der Vorst, T., & Jelicic, N. (2019). Artificial intelligence in education: Can AI bring the full potential of personalized learning to education? [Conference proceedings to be completed by the author(s)].

Verma, M. (2018). Educational technology and artificial intelligence for sustainable learning. [Journal details to be completed by the author(s)].