

From Traditional to AI-Enhanced Education a Consumer Behaviour Perspective on Student Preferences and Technology Adoption in Universities

Mrs. Rachna Saxena¹

¹Centre for Teaching, Learning and Development, Teerthanker Mahaveer University, Delhi Road, Moradabad-244001, Uttar Pradesh, India

Email: rachnasaxena7260@gmail.com

ABSTRACT

Universities are moving from traditional, instructor-centred delivery towards AI-enhanced education in which adaptive platforms, intelligent tutors, and generative AI assistants form part of everyday study. This paper examines that shift through a consumer behaviour lens, treating students as users and evaluators of an educational service whose adoption decisions are shaped by perceived usefulness, effort, social influence, enjoyment, value, risk, and habit. Drawing on technology acceptance theory, the theory of planned behaviour, the unified theory of acceptance and use of technology, diffusion of innovations, expectation-confirmation theory, and research on consumer resistance to innovation, the paper compares traditional and AI-enhanced education from the student's viewpoint, reviews empirical evidence on student acceptance of generative AI, and proposes a conceptual model with ten testable hypotheses and a measurement plan. It also describes a student decision journey and an adopter segmentation, and discusses implications for university strategy, teaching, and policy. The paper is conceptual and literature-based: it reports no primary survey data, and its tables and figures are syntheses of the cited sources. It concludes that students adopt AI where it offers clear value at low effort and acceptable risk, and that universities should treat adoption as a service-design and trust-building challenge rather than a purely technical one.

Keywords: consumer behaviour, student preferences, technology adoption, AI-enhanced education, UTAUT, higher education

1. INTRODUCTION

Higher education has long been delivered through lectures, textbooks, and scheduled contact with academics. Over the past decade, and especially since the public release of ChatGPT in late 2022, students have gained access to tools that explain concepts on demand, adapt practice to their level, and draft or critique their work (Zawacki-Richter, Marín, Bond, & Gouverneur, 2019; Kasneci et al., 2023). Reviews of the research literature now treat AI in higher education as a major and fast-growing field (Bond et al., 2024), and studies of student use of ChatGPT describe rapid and widespread uptake (Abdallah, Katmah, Khalaf, & Jelinek, 2025; Dikilitaş, Klippen, & Keles, 2024).

Most existing work asks whether AI improves learning. A complementary question is why students choose, or decline, to use it. Students decide freely and individually whether to open an AI tool before an assignment, and they do so by weighing benefits, effort, cost, peer behaviour, and risk, which are the same considerations that structure consumer decisions about products and services. A consumer behaviour perspective therefore offers a useful way to understand student preferences and to explain variation in adoption within the same course and institution.

This paper has four objectives: (1) to compare traditional and AI-enhanced education from the student's perspective; (2) to review the theories that explain technology adoption and consumer resistance and the

evidence on student acceptance of AI; (3) to propose a conceptual model with testable hypotheses and a measurement plan; and (4) to draw implications for universities. The paper is a structured narrative review of 25 sources. It is conceptual and does not present primary data; its tables and figures are syntheses of the cited literature, and the proposed model has not yet been empirically tested.

2. LITERATURE REVIEW

2.1 The Student As Consumer

The idea that students behave as consumers of higher education is long established in the marketing literature. Hemsley-Brown and Oplatka (2006) reviewed research on the marketing of universities and showed how institutions compete for students and how students evaluate and choose among them. The consumer framing is contested, however. Bunce, Baird, and Jones (2017) found that a stronger consumer orientation among students was associated with lower academic performance, suggesting that treating education as a purchased product can weaken the active effort learning requires. This tension is central to the present topic: AI tools that make study easier are attractive to consumer-minded students, yet ease is not the same as learning.

A consumer behaviour lens does not assume that education is only a commodity. It simply recognises that students make real choices about which resources to use, and that those choices follow identifiable psychological

patterns. Perceived value, defined by Zeithaml (1988) as an overall assessment of what is received relative to what is given, is a useful organising idea: students weigh time saved, grades, and understanding gained against effort, cost, and risks such as academic misconduct.

2.2 Traditional and AI-Enhanced Education

Attribute	Traditional education	AI-enhanced education
Availability of help	Limited to class hours, office hours, and peers	Available on demand at any time (Kasneci et al., 2023)
Pace and personalisation	Fixed pace set for the whole class	Adaptive pacing and tailored practice (Zawacki-Richter et al., 2019)
Feedback	Delayed, often after assessment	Immediate and iterative (Kasneci et al., 2023)
Human relationship	Direct contact with academics and peers	Mediated by a system; human contact may decrease
Effort and learning risk	Effort is built into the task	Easier to offload effort; risk of over-reliance (Fan et al., 2025)
Trust and risk	Established norms and credentials	Concerns about accuracy, privacy, bias, and integrity (Holmes et al., 2022)
Equity of access	Uniform access within the institution	Depends on devices, skills, and tool access

Source: Author's synthesis of the cited literature.

2.3 Theories of Technology Adoption

Several complementary theories explain why people adopt technologies. The Technology Acceptance Model holds that perceived usefulness and perceived ease of use shape intention to use a technology (Davis, 1989), and reviews have found it a credible and widely applied model in educational settings (Granić & Marangunić, 2019; Al-Emran, Mezhyuev, & Kamaludin, 2018). The theory of planned behaviour adds attitude, subjective norm, and perceived behavioural control (Ajzen, 1991). The unified

Compared

Table 1 contrasts the two models across attributes that matter to students as service users. The comparison is conceptual and draws on the reviews cited; it should not be read as measured performance data.

Table 1. Traditional and AI-enhanced education from the student's perspective

theory of acceptance and use of technology (UTAUT) integrates earlier models into four determinants: performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh, Morris, Davis, & Davis, 2003). Its extension, UTAUT2, was developed for consumer settings and adds hedonic motivation, price value, and habit (Venkatesh, Thong, & Xu, 2012). Table 2 summarises these frameworks and their relevance here.

Table 2. Theoretical frameworks used to explain student adoption of AI-enhanced education

Framework	Key constructs	Relevance to AI-enhanced education
Technology Acceptance Model (Davis, 1989)	Perceived usefulness; perceived ease of use	Do students find AI tools useful and easy to use for study?
Theory of Planned Behaviour (Ajzen, 1991)	Attitude; subjective norm; perceived behavioural control	Role of peer and teacher expectations and students' sense of control
UTAUT (Venkatesh et al., 2003)	Performance expectancy; effort expectancy; social influence; facilitating conditions	Core predictors of intention to use AI tools
UTAUT2 (Venkatesh et al., 2012)	Adds hedonic motivation, price value, habit	Consumer-style drivers such as enjoyment, cost, and routine use
Expectation-confirmation (Bhattacharjee, 2001)	Confirmation; satisfaction; continuance intention	Whether students keep using AI after initial trial

Framework	Key constructs	Relevance to AI-enhanced education
Diffusion of Innovations (Rogers, 2003)	Relative advantage; compatibility; complexity; trialability; observability	How AI spreads across student groups over time
Innovation resistance (Ram & Sheth, 1989)	Usage, value, and risk barriers; tradition and image barriers	Why some students and academics resist AI

Source: Author's synthesis of the cited literature.

2.4 Diffusion, Continuance, and Resistance

Rogers (2003) describes adoption as a process in which innovations spread through a social system over time, with groups of adopters differing in how early they adopt. Relative advantage, compatibility with existing practice, complexity, trialability, and observability determine the speed of adoption. Bhattacharjee (2001) argues that continued use depends on satisfaction, which in turn depends on whether expectations were confirmed after initial use. This is relevant to AI tools, because early enthusiasm may fade if outputs prove unreliable. Resistance is equally important. Ram and Sheth (1989) identify functional barriers (usage, value, and risk) and psychological barriers (tradition and image) that lead consumers to resist innovations. In universities these appear as concerns about accuracy and privacy, uncertainty about whether AI use will be treated as misconduct, and attachment to familiar ways of studying (Holmes et al., 2022; Dwivedi et al., 2023).

2.5 Evidence on Student Acceptance of Generative AI

Empirical work applying these theories to generative AI is growing. Strzelecki (2024), applying UTAUT2 to ChatGPT among university students, found that habit, performance expectancy, and hedonic motivation were among the significant predictors of behavioural intention, supporting the relevance of consumer-oriented constructs. Systematic reviews describe common student uses of ChatGPT for explanation, drafting, and feedback, along with concerns about integrity and accuracy (Abdallah et al., 2025; Dikilitaş et al., 2024). A meta-analysis of experimental studies found that ChatGPT interventions

generally improved academic performance and affective-motivational outcomes (Deng, Jiang, Yu, Lu, & Liu, 2025), which supports the perceived-benefit side of the decision.

There is also evidence for the risk side. Fan et al. (2025) found that students supported by ChatGPT improved short-term task performance yet showed reduced self-regulated learning, and Zhai, Wibowo, and Li (2024) report that over-reliance on AI dialogue systems can impair cognitive abilities. Long and Magerko (2020) argue that AI literacy is a distinct competency needed to use AI critically. Dwivedi et al. (2023) discuss the opportunities and challenges of ChatGPT from multiple perspectives, including concerns about originality and trust. Together this evidence suggests that adoption decisions involve a genuine trade-off, and that students' ability to judge that trade-off varies.

3. CONCEPTUAL MODEL AND HYPOTHESES

Building on UTAUT2, expectation-confirmation theory, the perceived value concept, and the resistance literature, the paper proposes the model in Figure 1. Behavioural intention to use AI-enhanced education is predicted by performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, perceived value, perceived risk, and AI literacy. Intention leads to actual use, and satisfaction after use drives continuance. Prior AI experience, discipline, gender, and year of study are proposed as moderators, following the moderator logic of UTAUT (Venkatesh et al., 2003). Habit is omitted from the model because it develops through repeated use, and is better treated as a predictor of continued use in longitudinal designs

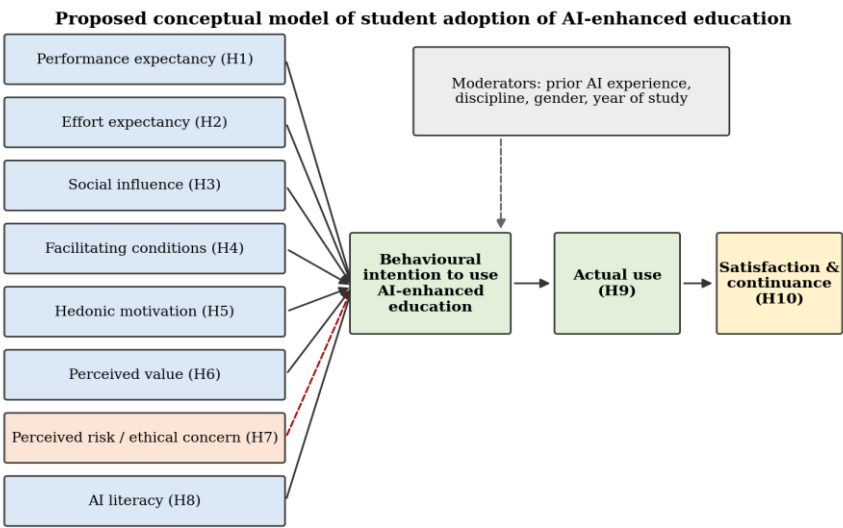


Figure 1. Proposed conceptual model of student adoption of AI-enhanced education (author's synthesis; not empirically tested).

The hypotheses and suggested measurement approach are shown in Table 3. Expected directions follow the theories cited; they are propositions to be tested, not findings

Table 3. Proposed hypotheses and measurement plan

No.	Hypothesis	Construct basis	Measurement (proposed)
H1	Performance expectancy positively affects behavioural intention	Venkatesh et al. (2003)	Multi-item scale Likert
H2	Effort expectancy positively affects behavioural intention	Venkatesh et al. (2003)	Multi-item scale Likert
H3	Social influence positively affects behavioural intention	Venkatesh et al. (2003)	Multi-item scale Likert
H4	Facilitating conditions positively affect behavioural intention	Venkatesh et al. (2003)	Multi-item scale Likert
H5	Hedonic motivation positively affects behavioural intention	Venkatesh et al. (2012)	Multi-item scale Likert
H6	Perceived value positively affects behavioural intention	Zeithaml (1988); Venkatesh et al. (2012)	Multi-item scale Likert
H7	Perceived risk negatively affects behavioural intention	Ram & Sheth (1989)	Multi-item scale Likert
H8	AI literacy positively affects behavioural intention	Long & Magerko (2020)	Self-report scale plus knowledge items
H9	Behavioural intention positively affects actual use	Venkatesh et al. (2003)	Reported frequency of use
H10	Satisfaction after use positively affects continuance intention	Bhattacharjee (2001)	Multi-item scale Likert

Source: Author's proposal based on the cited literature.

4. PROPOSED RESEARCH METHODOLOGY

A quantitative, cross-sectional survey design is proposed to test the model. The target population would be enrolled university students across several disciplines, sampled through stratified or quota methods so that year of study and discipline are represented. The questionnaire would adapt validated items from UTAUT and UTAUT2 studies to the context of AI tools for study, with additional items for perceived risk and AI literacy, and would use five- or seven-point Likert scales. A pilot test would be conducted before the main survey, and the instrument would be reviewed for content validity.

Data would be analysed with structural equation modelling, using either covariance-based or partial least squares approaches. The measurement model would be assessed for reliability and validity, using conventional thresholds such as Cronbach's alpha of at least 0.70,

followed by assessment of the structural model and tests of moderation by prior experience and discipline. Ethical approval, informed consent, and anonymity would be required, and respondents would be told that reporting AI use carries no academic penalty, to reduce social desirability bias. A follow-up wave would examine continuance and habit.

5. STUDENT DECISION JOURNEY AND ADOPTER SEGMENTS

Consumer behaviour research commonly describes decisions as a sequence of stages. Applied to AI-enhanced education, students move from awareness, through consideration and trial, to adoption and continuance, as shown in Figure 2. Barriers differ by stage: low awareness early on, perceived complexity and integrity concerns during consideration, and unmet expectations or loss of trust after use (Bhattacharjee, 2001; Ram & Sheth, 1989)

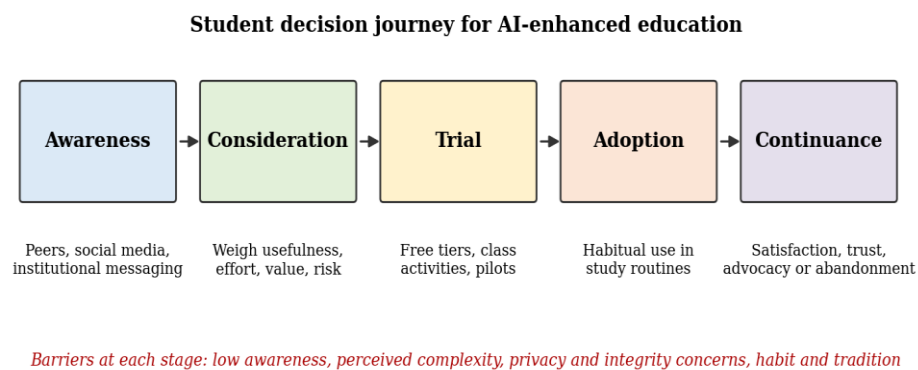


Figure 2. Student decision journey for AI-enhanced education (author's synthesis).

Rogers (2003) proposes that adopters in a social system fall into five categories whose proportions approximate a normal distribution over time, as illustrated in Figure 3.

The proportions are a theoretical benchmark from diffusion theory, not measured data for any university.

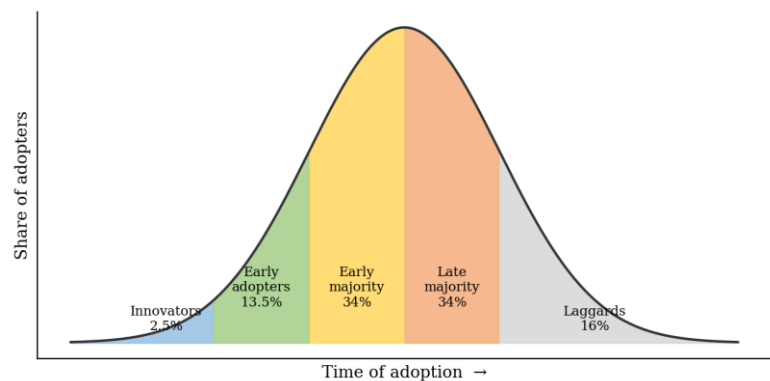


Figure 3. Rogers' adopter categories and their theoretical proportions (Rogers, 2003).

Table 4 translates these categories into student segments and corresponding institutional approaches. The segment

descriptions are illustrative hypotheses derived from diffusion theory and the resistance literature

Table 4. Illustrative student segments and institutional responses

Segment	Likely characteristics (hypothesised)	Institutional response
Innovators	Experiment with new tools early; high technical confidence	Involve in pilots and peer-mentoring; guide towards responsible use
Early adopters	Opinion leaders who quickly see relative advantage	Use as visible examples; gather feedback on tools and policy
Early majority	Adopt once usefulness is proven and peers use it	Provide demonstrations, trials, and clear guidance
Late majority	Cautious; influenced by norms and perceived risk	Offer clear policies, training, and reassurance on privacy and integrity
Laggards	Attached to established methods; resistant to change	Keep non-AI options; address concerns and avoid compulsion

Source: Author's synthesis based on Rogers (2003) and Ram & Sheth (1989).

6. DISCUSSION AND IMPLICATIONS

6.1 Implications for University Strategy

If students act as consumers, then the value proposition of AI-enhanced education must be clear to them. Universities should communicate concretely what approved tools do, what they cost, and how they fit into assessment, because perceived value and perceived risk shape intention (Zeithaml, 1988; Ram & Sheth, 1989). Reducing effort barriers through single sign-on access, training, and technical support addresses effort expectancy and facilitating conditions, while visible peer and teacher endorsement addresses social influence. UNESCO (2023) recommends that institutions set clear policies and invest in AI literacy, which directly reduces the uncertainty that fuels resistance.

6.2 Implications for Teaching and Learning

The consumer framing carries a caution. Because ease of use is attractive, students may adopt AI in ways that reduce effort without improving learning (Bunce et al., 2017; Fan et al., 2025). Academics should therefore design tasks in which AI use supports reasoning, for example by requiring students to evaluate and verify AI output, and should assess process as well as product. Adoption is not an end in itself; the aim is learning gain, and satisfaction should be judged against that aim.

6.3 Implications for Equity and Governance

Facilitating conditions are unevenly distributed. Students with better devices, connectivity, and digital skills are better placed to benefit, which may widen existing gaps, as Capraro et al. (2024) warn in a broader analysis of generative AI. Ethical safeguards covering privacy, bias, and transparency are therefore part of the adoption problem, not an afterthought (Holmes et al., 2022). Institutions that earn students' trust on these matters are likely to see more sustained use.

7. LIMITATIONS AND FUTURE RESEARCH

REFERENCES

1. Abdallah, N., Katmah, R., Khalaf, K., & Jelinek, H. F. (2025). Systematic review of ChatGPT in higher education: Navigating impact on learning, wellbeing, and collaboration. *Social Sciences & Humanities Open*, 12, Article 101866.
2. Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179–211.
3. Al-Emran, M., Mezhuyev, V., & Kamaludin, A. (2018). Technology Acceptance Model in M-learning context: A systematic review. *Computers & Education*, 125, 389–412.
4. Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly*, 25(3), 351–370.
5. Bond, M., Khosravi, H., De Laat, M., Bergdahl, N., Negrea, V., Oxley, E., Pham, P., Chong, S. W., &

This paper is a narrative review and does not follow systematic search procedures, so relevant work may be missing and source selection reflects the author's judgement. It reports no primary data. The tables, the segmentation, and the conceptual model are interpretive syntheses, and the ten hypotheses have not been tested. Much of the evidence on generative AI is recent, short-term, and often self-reported, and findings may not transfer to newer systems or to other cultural and institutional settings. The consumer perspective itself is contested and may understate the educational purposes of university study (Bunce et al., 2017).

Future research should test the proposed model with survey data and structural equation modelling, compare results across disciplines, institutions, and countries, and use longitudinal designs to study habit, satisfaction, and continuance. Mixed-methods studies could explore why students resist AI, and experimental work could test whether interventions such as AI literacy training change adoption quality as well as adoption rates.

8. CONCLUSION

This paper examined the shift from traditional to AI-enhanced education through a consumer behaviour lens. Drawing on technology acceptance, planned behaviour, UTAUT and UTAUT2, diffusion, expectation-confirmation, and resistance theories, it argued that students adopt AI tools when they perceive clear value at low effort, receive social and institutional support, and judge the risks acceptable. It proposed a conceptual model with ten hypotheses, a measurement plan, a decision journey, and an adopter segmentation.

The consumer perspective is useful but incomplete. Easy and enjoyable tools can be adopted quickly without improving learning, so universities must pair attention to student preferences with pedagogical design, AI literacy, and ethical governance. Treating adoption as a service-design and trust-building challenge, while keeping learning outcomes as the measure of success, offers a balanced route from traditional to AI-enhanced education. Empirical testing of the proposed model is the next step.

8. Siemens, G. (2024). A meta systematic review of artificial intelligence in higher education: A call for increased ethics, collaboration, and rigour. *International Journal of Educational Technology in Higher Education*, 21, Article 4.
9. Bunce, L., Baird, A., & Jones, S. E. (2017). The student-as-consumer approach in higher education and its effects on academic performance. *Studies in Higher Education*, 42(11), 1958–1978.
10. Capraro, V., Lentsch, A., Acemoglu, D., et al. (2024). The impact of generative artificial intelligence on socioeconomic inequalities and policy making. *PNAS Nexus*, 3(6), Article pgae191.
11. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340.
12. Deng, R., Jiang, M., Yu, X., Lu, Y., & Liu, S. (2025). Does ChatGPT enhance student learning? A systematic review and meta-analysis of experimental studies. *Computers & Education*, 227, Article 105224.

13. Dikilitaş, K., Klippen, M. I. F., & Keles, S. (2024). A systematic rapid review of empirical research on students' use of ChatGPT in higher education. *Nordic Journal of Systematic Reviews in Education*, 2(1).
14. Dwivedi, Y. K., Kshetri, N., Hughes, L., et al. (2023). Opinion paper: "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, 71, Article 102642.
15. Fan, Y., Tang, L., Le, H., Shen, K., Tan, S., Zhao, Y., Shen, Y., Li, X., & Gašević, D. (2025). Beware of metacognitive laziness: Effects of generative artificial intelligence on learning motivation, processes, and performance. *British Journal of Educational Technology*, 56(2), 489–530.
16. Granić, A., & Marangunić, N. (2019). Technology acceptance model in educational context: A systematic literature review. *British Journal of Educational Technology*, 50(5), 2572–2593.
17. Hemsley-Brown, J., & Oplatka, I. (2006). Universities in a competitive global marketplace: A systematic review of the literature on higher education marketing. *International Journal of Public Sector Management*, 19(4), 316–338.
18. Holmes, W., Porayska-Pomsta, K., Holstein, K., et al. (2022). Ethics of AI in education: Towards a community-wide framework. *International Journal of Artificial Intelligence in Education*, 32, 504–526.
19. Kasneci, E., Sessler, K., Küchemann, S., et al. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, 103, Article 102274.
20. Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1–16). ACM.
21. Ram, S., & Sheth, J. N. (1989). Consumer resistance to innovations: The marketing problem and its solutions. *Journal of Consumer Marketing*, 6(2), 5–14.
22. Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.
23. Strzelecki, A. (2024). To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology. *Interactive Learning Environments*, 32(9), 5142–5155.
24. UNESCO. (2023). *Guidance for generative AI in education and research*. UNESCO Publishing.
25. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478.
26. Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157–178.
27. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education: Where are the educators? *International Journal of Educational Technology in Higher Education*, 16, Article 39.
29. Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence. *Journal of Marketing*, 52(3), 2–22.
30. Zhai, C., Wibowo, S., & Li, L. D. (2024). The effects of over-reliance on AI dialogue systems on students' cognitive abilities: A systematic review. *Smart Learning Environments*, 11, Article 28.