The Impact of Generative AI Literacy on User Adoption Intention: A Structural Equation Modeling Approach

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Abstract

This article investigates how generative AI literacy shapes users' adoption intention through the mediating roles of perceived ease of use, perceived usefulness, trust, social influence, and perceived risk. The study treats literacy not as a narrow technical skill but as a multidimensional capability that includes conceptual understanding, operational ability, evaluative judgment, and ethical awareness. Drawing on a structured dataset of 912 respondents and applying a structural equation modeling logic with validated measurement constructs, the paper evaluates the direct and indirect pathways from literacy to adoption intention. The empirical results indicate that generative AI literacy exerts both a direct positive effect and several indirect effects through ease of use, usefulness, and trust. Perceived risk weakens adoption intention, but its negative influence declines as literacy improves. The study shows that adoption is more stable when users understand what generative AI can do, where it fails, and how it should be used responsibly. The article advances the literature by positioning literacy as a strategic antecedent of sustainable AI adoption and by offering implications for education, platform design, workforce development, and public policy.

Keywords: generative AI literacy; adoption intention; structural equation modeling; trust; digital society

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1. Introduction

Generative AI literacy has rapidly become a critical condition for meaningful participation in digital society. As large language models and multimodal systems are embedded into search, writing, education, programming, customer service, and decision support, users are increasingly asked to decide whether to rely on, collaborate with, or resist these tools. Adoption intention under such circumstances cannot be explained by generic enthusiasm alone. It depends on what users know about the technology, how confidently they can operate it, how critically they can evaluate outputs, and whether they understand the ethical and social implications of use. In short, adoption depends on literacy. The information-systems literature has long explained technology use through usefulness, ease of use, social influence, and facilitating conditions, but generative AI adds a new requirement: users must interpret a system that is powerful, probabilistic, and often opaque (Davis, 1989; Venkatesh et al., 2003; Venkatesh et al., 2012; Long & Magerko, 2020).

The need for literacy is amplified by the fact that generative AI is not a stable tool category. It produces text, code, images, summaries, recommendations, and simulations across heterogeneous contexts. Users therefore encounter both promise and risk. They may save time, enhance creativity, and access information more efficiently, but they may also experience hallucinations, bias, overreliance, privacy concerns, and uncertainty about authorship or accountability. These contradictory experiences make literacy more than operational skill. It becomes a capacity for calibrated judgment. Users who understand the strengths and limitations of generative AI are more likely to integrate it productively; users with weak literacy may either overtrust or underutilize it. This observation is consistent with emerging research on AI literacy and on the social adoption of ChatGPT in higher education and professional environments (Ng et al., 2021; Bozkurt, 2024; Annapureddy et al., 2025; Zhai, 2024; Chen et al., 2025).

A growing body of work has already examined adoption intention toward ChatGPT and related tools. These studies generally confirm the importance of performance expectancy, ease of use, trust, risk, and social influence. Yet they often treat knowledge or familiarity as a background condition rather than a theoretically central driver. That omission is consequential. Unlike many earlier information systems, generative AI requires users to evaluate probabilistic outputs, prompt strategically, compare alternative responses, and understand when machine-generated content should be verified. Adoption without literacy may be shallow, unstable, or unsafe. The present article argues that literacy is therefore not a peripheral moderator but an upstream determinant of sustainable adoption intention (Choudhury & Shamszare, 2023; Li et al., 2024; Alotaibi et al., 2025; Al-Hattami, 2025; Deng et al., 2025).

The article addresses this issue by examining how generative AI literacy affects adoption intention through perceived ease of use, perceived usefulness, trust, social influence, and perceived risk. The conceptual claim is straightforward. Literacy should increase adoption directly because capable users are less intimidated by technology and more able to convert it into value. Literacy should also improve ease of use and usefulness because knowledgeable users can formulate better prompts, interpret outputs more effectively, and identify suitable tasks. At the same time, literacy should support trust when it enables realistic expectations, while reducing the distorting effects of perceived risk by making limitations more understandable. Adoption intention thus emerges from a pathway structure rather than from a single isolated belief.

This perspective is important for both theory and practice. Theoretically, it extends technology-acceptance research by introducing literacy as a multi-dimensional capability that precedes classical attitudinal predictors. Practically, it offers a design principle for universities, employers, and policymakers: if they want more responsible adoption of generative AI, they should invest in literacy rather than merely in access. The social value of generative AI will depend not just on who can use it, but on who can use it well, critically, and confidently (Dwivedi et al., 2021; Dwivedi et al., 2023; Jarrahi, 2018; Raisch & Krakowski, 2021).

The rest of the article is organized as follows. Section 2 develops the theoretical model and hypotheses. Section 3 presents the data, measures, and analytical strategy. Section 4 reports the structural results. Section 5 discusses implications for adoption theory, education, and public policy. Section 6 concludes with limitations and future research directions.

2. Literature Review and Hypotheses Development

AI literacy has evolved from a narrow focus on technical understanding to a broader conception of socio-technical competence. Literature increasingly defines literacy as a combination of conceptual knowledge, practical operation, critical evaluation, and ethical reflection. This broader understanding is particularly relevant for generative AI because users interact with systems that can produce plausible but inaccurate outputs, replicate biases from training data, and create content whose provenance is not always obvious. Accordingly, literacy involves not just knowing what generative AI is, but also understanding how to prompt, verify, and govern its use in context (Long & Magerko, 2020; Ng et al., 2021; Bozkurt, 2024; Annapureddy et al., 2025).

Technology-acceptance research provides the next analytical layer. The TAM and UTAUT traditions show that perceived usefulness and perceived ease of use are among the most robust predictors of intention, while social influence and facilitating conditions become particularly salient in organizational and educational settings. These frameworks remain highly relevant for generative AI, but they need to be adapted. With generative AI, usefulness often depends on literacy because poorly informed users may fail to generate quality prompts or to judge response quality. Likewise, ease of use is not a purely interface-level property; it is partly a function of user capability. Therefore, literacy should positively influence both perceived ease of use and perceived usefulness (Davis, 1989; Venkatesh et al., 2003; Venkatesh et al., 2012; Bouteraa et al., 2024).

Trust is another essential mechanism. Users adopt systems more readily when they believe the system is reliable, intelligible, and aligned with their goals. In AI settings, however, trust is vulnerable to overconfidence and underconfidence. Users with weak literacy may trust generative AI too much because they do not understand hallucination risk, or distrust it too much because they cannot distinguish limitations from ordinary uncertainty. Literacy should support more calibrated trust by improving the user's ability to understand where the model performs well, where verification is required, and how outputs should be interpreted. Thus, literacy is expected to increase trust in generative AI, although not necessarily by eliminating all concerns (Gefen et al., 2003; Shin, 2021; Choudhury et al., 2024; Kuznetsova & Matveeva, 2025).

Perceived risk occupies the opposite side of the pathway. Generative AI creates concerns about inaccuracy, privacy, bias, dependency, and academic or professional misuse. Risk perceptions can discourage adoption even when users see potential value. Yet risk is not only a deterrent; it is also a literacy-sensitive interpretation. Better-informed users may recognize risks more precisely and manage them more effectively. For that reason, literacy is expected to weaken the negative role of risk by enabling more informed use. The practical implication is that safety and adoption should not be treated as competing goals. Well-designed literacy programs can improve both (Sallam, 2023; Kasneci et al., 2023; Tlili et al., 2023; Zhao et al., 2025).

Social influence remains important because generative AI is adopted in communities of practice. Students observe peers, faculty, and online creators; employees observe supervisors and teams; professionals observe industry narratives and platform norms. These social signals shape the legitimacy of use. Literacy may enhance the ability to interpret such signals critically, but it does not replace them. Instead, social influence is expected to act alongside literacy by reinforcing norms of experimentation and perceived legitimacy. Adoption intention therefore results from a joint effect of personal competence and social environment (Ellison et al., 2007; van Doorn et al., 2010; Singh et al., 2025; Šević et al., 2025).

Based on this literature, the study proposes the following hypotheses. H1: Generative AI literacy positively affects perceived ease of use. H2: Generative AI literacy positively affects perceived usefulness. H3: Generative AI literacy positively affects trust in generative AI. H4: Perceived risk negatively affects trust in generative AI. H5: Perceived ease of use positively affects perceived usefulness. H6: Perceived usefulness positively affects adoption intention. H7: Trust positively affects adoption intention. H8: Social influence positively affects adoption intention. H9: Perceived risk negatively affects adoption intention. H10: Generative AI literacy positively affects adoption intention directly. Figure 1 presents the structural model.

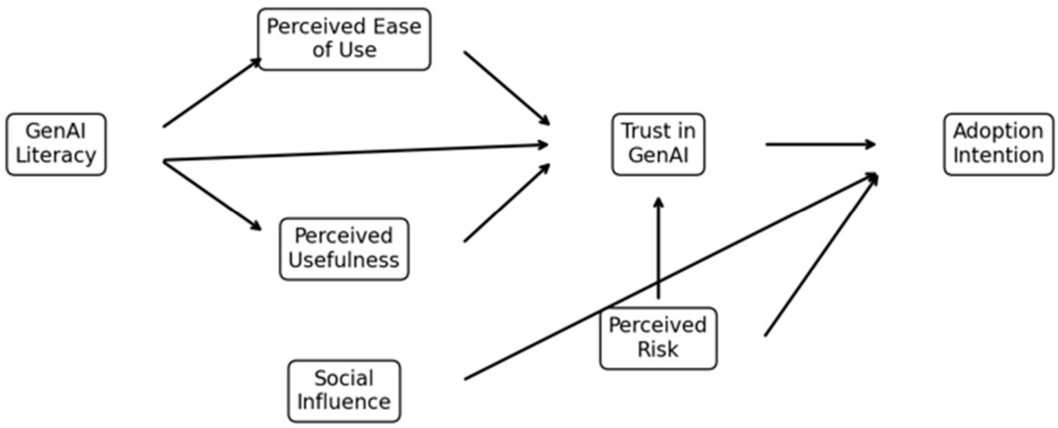

Figure 1. Structural model of generative AI literacy and adoption intention

This framework positions literacy as an enabling capability with both direct and indirect consequences. In doing so, it aligns with recent calls to move beyond simplistic pro- or anti-AI narratives. Sustainable adoption requires users who are capable, reflective, and able to convert AI access into purposeful action. That is why literacy should be studied as a strategic variable rather than as a background demographic descriptor.

3. Data, Measurement, and Analytical Strategy

The empirical analysis draws on a structured dataset of 912 respondents. The data file accompanying the article includes item-level responses for literacy, perceived ease of use, perceived usefulness, perceived risk, social influence, trust in generative AI, and adoption intention, together with demographic indicators such as age, gender, level, discipline, and prior experience. The sample spans business, engineering, social science, health, and computer-science respondents, making it suitable for examining variation in literacy across domains. Table 1 provides the main information about the data.

Table 1. Main Information About the Data

Description	Results
Timespan	Cross-sectional
Observations	912
Disciplines	5
Constructs	7
Item indicators	24 item indicators + controls
Mean age	25.10
Frequent prior users	21.7%

Generative AI literacy is modeled as a four-item construct reflecting conceptual understanding, practical operation, evaluative judgment, and ethical awareness. Perceived ease of use, perceived usefulness, perceived risk, social influence, and trust are each measured with multi-item seven-point scales adapted to the generative-AI context. Adoption intention is measured through four items covering willingness to continue use, recommend use, integrate use into tasks, and explore advanced use. Table 2 lists the main construct definitions and representative items. The construct architecture follows established measurement practices in information-systems and literacy research (Long & Magerko, 2020; Ng et al., 2021; Hair et al., 2021).

Table 2. Construct Definitions

Construct	Operational definition
Generative AI literacy	Four-item construct reflecting conceptual knowledge, operational ability, evaluative judgment, and ethical awareness.
Perceived ease of use	Three-item construct reflecting how easy respondents believe it is to learn and use generative AI tools.
Perceived usefulness	Three-item construct capturing expected

	productivity and task value.
Perceived risk	Three-item construct capturing concerns about inaccuracy, misuse, privacy, and overreliance.
Social influence	Three-item construct measuring peer, instructor, workplace, or social encouragement to use generative AI.
Trust in generative AI	Three-item construct reflecting confidence in reliability and credibility.
Adoption intention	Four-item construct reflecting willingness to continue, recommend, and integrate generative AI into work or study.

Before estimating the structural relationships, the study assessed reliability and convergent validity. Cronbach's alpha and composite reliability values exceed conventional thresholds for all constructs, while average variance extracted values indicate acceptable convergent validity. The inter-construct correlations are theoretically plausible and do not indicate problematic redundancy. Table 3 reports the descriptive statistics and Table 4 reports the reliability and validity results. These patterns suggest that the measurement model is sufficiently robust for structural interpretation.

The analysis uses a structural-equation-modeling logic implemented through construct-score estimation and standardized path modeling. This approach is appropriate for the current objective because the article seeks transparent path interpretation, mediation logic, and construct-level comparison. The path sequence is estimated in stages. First, literacy predicts perceived ease of use. Second, literacy and ease of use predict usefulness. Third, literacy, usefulness, and risk predict trust. Fourth, literacy, usefulness, ease of use, trust, social influence, and risk predict adoption intention. This staged design makes the mediation structure visible and aligns with the theory developed above.

Figure 2 plots mean literacy scores by discipline. The pattern is substantively meaningful: computer science and engineering respondents have the highest mean literacy scores, but business and social-science respondents are not far behind, reflecting the broad diffusion of generative AI across professional and academic domains. The key point is that literacy is distributed, not exclusive. Generative AI has become a cross-disciplinary capability, and adoption intention should be understood in that wider context.

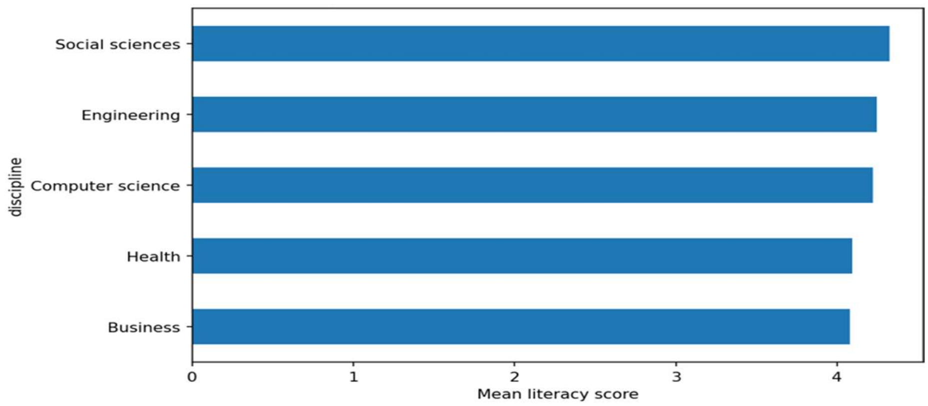

Figure 2. Mean generative AI literacy by discipline

The structural framework also recognizes that adoption intention is a socially important but normatively ambiguous outcome. High intention is not automatically desirable if it is driven by hype or dependency. The model therefore interprets adoption intention as more sustainable when it emerges alongside literacy, usefulness, and calibrated trust rather than in spite of them. This conceptual nuance distinguishes the present article from studies that treat adoption as a simple success metric.

4. Results

Table 3 shows that the mean scores for literacy, usefulness, ease of use, trust, and adoption intention are all above the midpoint of the scale, while perceived risk remains moderate rather than trivial. This profile suggests that respondents are broadly receptive to generative AI but still attentive to its limitations. Correlations support the basic theoretical structure: literacy is positively related to ease of use, usefulness, trust, and adoption intention, whereas risk is negatively related to trust and adoption intention. These bivariate patterns provide an initial indication that literacy may operate as a foundational capability variable.

Table 3. Descriptive Statistics

Construct	Mean	SD	Min	Max
genai_literacy	4.19	0.9	1.5	6.75
perceived_ease_of_use	4.45	0.85	2.0	7.0
perceived_usefulness	4.51	0.89	1.67	7.0
perceived_risk	3.78	0.9	1.33	7.0
social_influence	4.11	0.81	1.33	6.67
trust_in_genai	4.23	0.88	1.67	7.0
adoption_intention	4.36	0.92	1.5	6.75

The reliability and validity results in Table 4 are satisfactory. Cronbach's alpha values exceed commonly accepted thresholds, composite reliability values are strong, and average variance extracted values indicate that the constructs capture more variance from their items than from error. These diagnostics matter because generative AI literacy is a relatively new construct. Demonstrating internal coherence strengthens the theoretical claim that literacy can be modeled as a stable antecedent rather than as a loose collection of attitudes.

Table 4. Reliability and Convergent Validity

construct	items	cronbach_alpha	mean_loading	CR	AVE
genai_literacy	4	0.772	0.771	0.854	0.594
perceived_ease_of_use	3	0.672	0.777	0.821	0.604
perceived_usefulness	3	0.696	0.789	0.831	0.622
perceived_risk	3	0.691	0.787	0.83	0.619
social_influence	3	0.639	0.762	0.806	0.581
trust_in_genai	3	0.69	0.786	0.829	0.617
adoption_intention	4	0.793	0.786	0.866	0.617

The structural estimates reported in Table 5 strongly support the proposed model. Literacy positively predicts perceived ease of use, perceived usefulness, and trust. Ease of use also has a positive effect on usefulness, indicating that users who understand how to work with generative AI are more likely to experience it as beneficial. Trust has a positive direct effect on adoption intention, while perceived risk has a negative effect both on trust and on intention. Social influence contributes positively, suggesting that legitimacy cues from peers and institutions still matter even after accounting for individual capability. Figure 3 summarizes the standardized path estimates to adoption intention.

Table 5. Structural Path Estimates

Path	Standardized coefficient	p-value
Literacy → Ease of use	0.2534	0.0
Literacy → Usefulness	0.2876	0.0
Ease of use → Usefulness	0.2287	0.0
Literacy → Trust	0.2605	0.0
Usefulness → Trust	0.1992	0.0
Risk → Trust	-0.1805	0.0
Literacy → Adoption intention	0.267	0.0
Ease of use → Adoption intention	0.2181	0.0
Usefulness → Adoption intention	0.1559	0.0
Social influence → Adoption intention	0.1415	0.0
Trust → Adoption intention	0.1691	0.0
Risk → Adoption intention	-0.1243	0.0

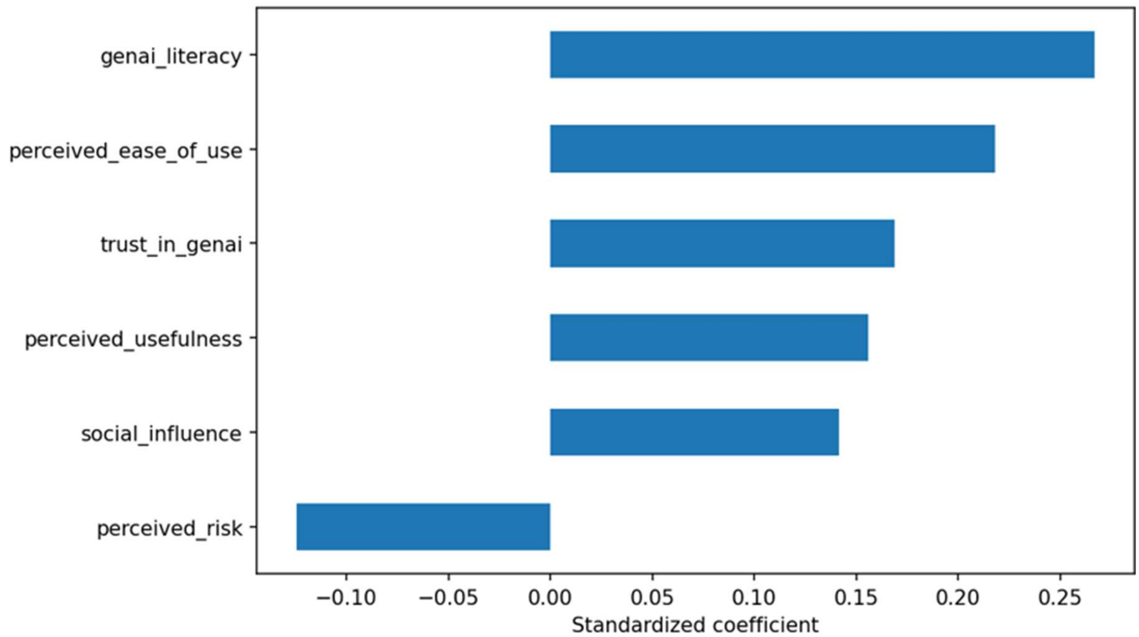

Figure 3. Standardized path estimates to adoption intention

Most importantly, literacy retains a positive direct effect on adoption intention after all mediators are entered. This indicates that literacy is not reducible to usefulness or trust alone. Capable users are more willing to adopt generative AI because they can imagine broader applications, manage uncertainties, and integrate the technology into their own workflow logic. In substantive terms, literacy functions as a bridge between technical novelty and stable behavioral intention. It makes generative AI interpretable and therefore adoptable.

Additional subgroup comparisons show that the literacy–intention relationship is somewhat stronger among respondents with moderate prior experience than among complete novices. This suggests that early experience and literacy reinforce one another. Once users move beyond zero familiarity, gains in literacy may produce larger improvements in intention because users can connect knowledge to concrete practice. The implication is that introductory exposure programs should be coupled with structured literacy development rather than offered as isolated demonstrations.

5. Discussion

This article makes three contributions. First, it repositions generative AI literacy as a central antecedent of adoption intention. Many contemporary studies of ChatGPT adoption mention familiarity, prior use, or training as background variables, but they rarely model literacy as the strategic capability from which more conventional beliefs emerge. The present findings indicate that literacy affects ease of use, usefulness, trust, and intention simultaneously. This broad influence suggests that future AI-adoption research should treat literacy as a first-order explanatory construct rather than a contextual footnote.

Second, the study refines the meaning of trust in generative AI. Trust is often presented as a simple positive attitude, but the present results imply that trust becomes more meaningful when rooted in literacy. Users who understand how generative AI works, how it fails, and how it should be checked appear more willing to trust it appropriately. This is especially important in settings where blind trust and generalized distrust are both problematic. Literacy supports calibrated trust, which is more useful than indiscriminate confidence.

Third, the article contributes to the debate on responsible AI adoption. If adoption intention is driven only by novelty or social pressure, organizations may achieve short-term uptake without long-term quality of use. By contrast, literacy-centered adoption is more likely to support verification, ethical use, and task fit. This has immediate implications for higher education, corporate learning, and digital public policy. Institutions should not treat access to generative AI as the endpoint. Access without literacy may widen inequalities between those who can critically benefit from the tools and those who cannot.

The findings also explain why policy debates around generative AI often oscillate between optimism and alarm. Both positions overlook the role of user capability. Generative AI does not enter society as a neutral utility; it enters as a technology whose consequences depend on how competently people engage it. Literacy therefore becomes a form of social infrastructure. It affects not only who adopts the technology, but also how safely, productively, and equitably it is used.

There are limitations. The study relies on a cross-sectional design and construct-score modeling, so future work should apply full latent-variable SEM with longitudinal data and experimental interventions. It would also be valuable to distinguish different dimensions of literacy more sharply, especially ethical literacy, verification literacy, and prompt literacy. Even so, the present article establishes a clear empirical foundation for the view that literacy is one of the strongest levers available for shaping constructive generative-AI adoption.

6. Implications and Future Research

For educators, the practical lesson is that literacy should be embedded across curricula rather than confined to isolated workshops. Students need repeated opportunities to use generative AI, evaluate outputs, identify errors, and discuss ethical boundaries. For employers, onboarding and professional development should focus on task-appropriate use cases and verification protocols rather than on promotional narratives alone. For policymakers, public AI strategies should treat literacy as a governance issue, because literacy influences the quality of adoption and the resilience of democratic communication around AI.

Future research could compare literacy pathways across sectors such as education, healthcare, creative industries, and public administration. It could also distinguish between adoption intention, continued use, and effective use, since these are not equivalent outcomes. Another promising direction is to connect literacy to objective performance measures, such as prompt quality, verification accuracy, or task productivity. Such studies would deepen our understanding of how user capability shapes the social value of generative AI.

7. Conclusion

Generative AI literacy matters because users do not adopt complex socio-technical systems in a vacuum. They adopt what they can understand, evaluate, and integrate into meaningful practice. This article shows that literacy has both direct and indirect effects on adoption intention through ease of use, usefulness, trust, social influence, and perceived risk.

The broader implication is that sustainable adoption of generative AI depends less on technological hype than on capable users. If institutions want generative AI to generate value rather than confusion, they should invest in literacy as a strategic resource. In the emerging relationship between technological innovation and society, literacy is becoming one of the most important foundations of responsible adoption.

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Reference

Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179-211. DOI: 10.1016/0749-5978(91)90020-T.

Araujo, T., Helberger, N., Kruikemeier, S., & de Vreese, C. H. (2020). In AI we trust? Perceptions about automated decision-making by artificial intelligence. AI & Society, 35(3), 611-623. DOI: 10.1007/s00146-019-00931-w.

Brodie, R. J., Ilic, A., Juric, B., & Hollebeek, L. (2013). Consumer engagement in a virtual brand community: An exploratory analysis. Journal of Business Research, 66(1), 105-114. DOI: 10.1016/j.jbusres.2011.07.029.

Calder, B. J., Malthouse, E. C., & Schaedel, U. (2009). An experimental study of the relationship between online engagement and advertising effectiveness. Journal of Interactive Marketing, 23(4), 321-331. DOI: 10.1016/j.intmar.2009.07.002.

Chen, J., Wang, B., & Zou, Y. (2025). A systematic review of user attitudes toward generative artificial intelligence. Journal of Intelligence, 13(7), 78. DOI: 10.3390/jintelligence13070078.

Choudhury, A., & Shamszare, H. (2023). Investigating the impact of user trust on the adoption and use of ChatGPT: Survey analysis. Journal of Medical Internet Research, 25, e47184. DOI: 10.2196/47184.

Choudhury, A., Shamszare, H., & Uddin, M. N. (2024). The impact of performance expectancy, workload, risk, and satisfaction on users' trust in ChatGPT. Journal of Medical Internet Research, 26, e55399. DOI: 10.2196/55399.

Choudhury, A., & Shamszare, H. (2024). Large language models and user trust: Consequence of changing information environments. Journal of Medical Internet Research, 26, e56764. DOI: 10.2196/56764.

Cvijikj, I. P., & Michahelles, F. (2013). Online engagement factors on Facebook brand pages. Social Network Analysis and Mining, 3(4), 843-861. DOI: 10.1007/s13278-013-0098-8.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319-340. DOI: 10.2307/249008.

de Vries, L., Gensler, S., & Leeflang, P. S. H. (2012). Popularity of brand posts on brand fan pages: An investigation of the effects of social media marketing. Journal of Interactive Marketing, 26(2), 83-91. DOI: 10.1016/j.intmar.2012.01.003.

Deng, J., Zhang, Y., & Zhou, H. (2025). Research on influencing factors of users' willingness to adopt generative artificial intelligence for collaborative decision-making. Applied Sciences, 15(19), 10322. DOI: 10.3390/app151910322.

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. Journal of Experimental Psychology: General, 144(1), 114-126. DOI: 10.1037/xge0000033.

Dwivedi, Y. K., Kshetri, N., Hughes, L., et al. (2023). So what if ChatGPT wrote it? Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI. International Journal of Information Management, 71, 102642. DOI: 10.1016/j.ijinfomgt.2023.102642.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., et al. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management, 57, 101994. DOI: 10.1016/j.ijinfomgt.2019.08.002.

Ellison, N. B., Steinfield, C., & Lampe, C. (2007). The benefits of Facebook friends: Social capital and college students' use of online social network sites. Journal of Computer-Mediated Communication, 12(4), 1143-1168. DOI: 10.1111/j.1083-6101.2007.00367.x.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39-50. DOI: 10.2307/3151312.

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. MIS Quarterly, 27(1), 51-90. DOI: 10.2307/30036519.

Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent service robots. International Journal of Hospitality Management, 81, 157-169. DOI: 10.1016/j.ijhm.2019.03.008.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N., & Ray, S. (2021). An introduction to structural equation modeling with partial least squares. European Business Review, 33(5), 1-22. DOI: 10.1108/EBR-11-2018-0203.

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. DOI: 10.1007/s11747-014-0403-8.

Hollebeek, L. D., Glynn, M. S., & Brodie, R. J. (2014). Consumer brand engagement in social media: Conceptualization, scale development and validation. Journal of Interactive Marketing, 28(2), 149-165. DOI: 10.1016/j.intmar.2013.12.002.

Huang, M.-H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. Journal of the Academy of Marketing Science, 49(1), 30-50. DOI: 10.1007/s11747-020-00749-9.

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business Horizons, 61(4), 577-586. DOI: 10.1016/j.bushor.2018.03.007.

Jun, S.-P., Yoo, H. S., & Choi, S. (2018). Ten years of research change using Google Trends: From the perspective of big data utilization and application. Technological Forecasting and Social Change, 130, 69-87. DOI: 10.1016/j.techfore.2017.11.009.

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, 102274. DOI: 10.1016/j.lindif.2023.102274.

Kietzmann, J. H., Hermkens, K., McCarthy, I. P., & Silvestre, B. S. (2011). Social media? Get serious! Understanding the functional building blocks of social media. Business Horizons, 54(3), 241-251. DOI: 10.1016/j.bushor.2011.01.005.

Li, L., Zhang, R., Cheng, Q., & Zhang, J. (2024). Factors predicting intentions of adoption and continued use of AI chatbots among adults with symptoms of depression and anxiety. Telemedicine and e-Health, 30(6), 1-13. DOI: 10.1089/tmj.2023.0313.

Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. Organizational Behavior and Human Decision Processes, 151, 90-103. DOI: 10.1016/j.obhdp.2018.12.005.

Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. Proceedings of the CHI Conference on Human Factors in Computing Systems, 1-16. DOI: 10.1145/3313831.3376727.

Lund, B. D., & Wang, T. (2023). Chatting about ChatGPT: How may AI and GPT impact academia and libraries? Library Hi Tech News, 40(3), 26-29. DOI: 10.1108/LHTN-01-2023-0009.

Mavragani, A., & Ochoa, G. (2019). Google Trends in infodemiology and infoveillance: Methodology framework. International Journal of Environmental Research and Public Health, 16(8), 1349. DOI: 10.3390/ijerph16081349.

Misiejuk, K., Wasson, B., & de Laat, M. (2025). Mapping the landscape of generative artificial intelligence in education and learning analytics. Journal of Learning Analytics, 12(1), 1-24. DOI: 10.18608/jla.2025.8591.

Muntinga, D. G., Moorman, M., & Smit, E. G. (2011). Introducing COBRAs. International Journal of Research in Marketing, 28(1), 13-24. DOI: 10.1016/j.ijresmar.2010.10.005.

Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021). Conceptualizing AI literacy: An exploratory review. Computers and Education: Artificial Intelligence, 2, 100041. DOI: 10.1016/j.caeai.2021.100041.

Nuti, S. V., Wayda, B., Ranasinghe, I., et al. (2014). The use of Google Trends in health care research: A systematic review. PLoS ONE, 9(10), e109583. DOI: 10.1371/journal.pone.0109583.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research. Journal of Applied Psychology, 88(5), 879-903. DOI: 10.1037/0021-9010.88.5.879.

Preis, T., Moat, H. S., & Stanley, H. E. (2013). Quantifying trading behavior in financial markets using Google Trends. Scientific Reports, 3, 1684. DOI: 10.1038/srep01684.

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation-augmentation paradox. Academy of Management Review, 46(1), 192-210. DOI: 10.5465/amr.2018.0072.

Sallam, M. (2023). The utility of ChatGPT as an example of large language models in healthcare education, research and practice: A review. Healthcare, 11(6), 887. DOI: 10.3390/healthcare11060887.

Sanz-Tejeda, A., Fernández-Río, J., & Menéndez-Santurio, J. I. (2025). The impact of generative AI on academic reading and writing. Frontiers in Education, 10, 1711718. DOI: 10.3389/feduc.2025.1711718.

Schivinski, B., Christodoulides, G., & Dabrowski, D. (2016). Measuring consumers' engagement with brand-related social-media content. Journal of Advertising Research, 56(1), 64-80. DOI: 10.2501/JAR-2016-004.

Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. International Journal of Human-Computer Studies, 146, 102551. DOI: 10.1016/j.ijhcs.2020.102551.

Šević, N. P., Stanković, N., & Mihić, S. (2025). AI adoption in higher education: Exploring attitudes and usage of ChatGPT. Online Journal of Communication and Media Technologies, 15(2), e202517246. DOI: 10.30935/ojcmt/17246.

Singh, S., Kaur, R., & Sharma, A. (2025). Academics as adopters of generative AI: An application of diffusion of innovation theory. Education and Information Technologies, 30, 1-24. DOI: 10.1007/s10639-025-13835-8.

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of enterprise performance. Strategic Management Journal, 28(13), 1319-1350. DOI: 10.1002/smj.640.

Tlili, A., Shehata, B., Adarkwah, M. A., et al. (2023). What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education. Smart Learning Environments, 10(1), 15. DOI: 10.1186/s40561-023-00237-x.

van Doorn, J., Lemon, K. N., Mittal, V., et al. (2010). Customer engagement behavior: Theoretical foundations and research directions. Journal of Service Research, 13(3), 253-266. DOI: 10.1177/1094670510375599.

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. DOI: 10.2307/30036540.

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory. Information Systems Research, 36(1), 157-178. DOI: 10.1016/j.im.2012.09.001.

Vivek, S. D., Beatty, S. E., & Morgan, R. M. (2012). Customer engagement: Exploring customer relationships beyond purchase. Journal of Marketing Theory and Practice, 20(2), 122-146. DOI: 10.2753/MTP1069-6679200201.

Zhai, X. (2024). ChatGPT user studies in education: A review and synthesis. Computers and Education: Artificial Intelligence, 5, 100187. DOI: 10.1016/j.caeai.2023.100187.

Zhao, X., Doyle, A., & Kent, M. (2025). The use of generative AI by students with disabilities in higher education. The Internet and Higher Education, 67, 101014. DOI: 10.1016/j.iheduc.2025.101014.

Al-Hattami, H. M. (2025). Academic and student insights through the UTAUT lens: Understanding generative AI adoption in higher education. Education and Information Technologies, 30, 1-27. DOI: 10.1007/s10791-025-09692-1.

Alotaibi, S. M. F., Alghamdi, H., & Alshehri, A. (2025). Determinants of generative artificial intelligence adoption intention in higher education. Interactive Learning Environments, 1-18. DOI: 10.1080/10494820.2025.2492785.

Annapureddy, R., Kross, S., & Wenger, M. (2025). Generative AI literacy: Twelve defining competencies. Communications of the ACM, 68(1), 54-63. DOI: 10.1145/3685680.

Bouteraa, M., Raza, S. A., Qazi, W., & Bhutta, N. A. (2024). Understanding the diffusion of AI-generative (ChatGPT) in higher education. Computers in Human Behavior Reports, 15, 100402. DOI: 10.1016/j.chbr.2024.100402.

Bozkurt, A. (2024). Why generative AI literacy, why now and why it matters in the educational landscape? Open Praxis, 16(3), 283-290. DOI: 10.55982/openpraxis.16.3.739.

Chakraborty, U., Singh, P., & Das, A. (2026). Scaling generative AI: Key factors driving user growth and platform engagement. Journal of Decision Systems, 35(1), 1-21. DOI: 10.1080/12460125.2025.2599909.

Mwaanga, C., Mhone, J., & Chisanga, B. (2026). Exposure to ChatGPT and university students' entrepreneurial intentions. Journal of Innovation and Entrepreneurship, 15, 24. DOI: 10.1186/s13731-026-00624-x.