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THE ROLE OF LOGICAL BELIEFS IN PREDICTING CHATGPT ADOPTION AND AVOIDANCE IN HIGHER EDUCATION

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Abstract
This conceptual research paper examines how logical beliefs—defined here as cognitive, evidential, and epistemic judgments about an innovation—shape both the adoption and avoidance of ChatGPT in higher education. While current debates emphasize ethical risks, skill impacts, and institutional policy, less attention has been paid to how faculty and students form reasoned beliefs about ChatGPT's reliability, usefulness, and limits, and how those beliefs translate into behavioural intentions. Integrating Theory of Planned Behavior (Ajzen, 1991), the Technology Acceptance Model (Davis, 1989), and scholarship on epistemic beliefs (Hofer & Pintrich, 1997), this paper develops a theoretical model in which logical beliefs (accuracy beliefs, transparency beliefs, evidential beliefs, and boundary beliefs) influence perceived usefulness, perceived ease of use, normative pressure, and perceived behavioral control, and thereby predict both adoption and conscious avoidance. The paper proposes an empirical mixed-methods design to test the model in multiple higher-education contexts, outlines measurement approaches, and discusses implications for policy, instructional design, and faculty development. Practical recommendations for institutions to reduce unwarranted avoidance and to ensure responsible uptake are provided. Limitations and future research directions are discussed.

Keywords: *ChatGPT, logical beliefs, technology adoption, avoidance, higher education, epistemic beliefs, TAM, TPB*

Introduction

The rapid uptake of large language models (LLMs) such as ChatGPT in late 2022–2024 has created both enthusiasm and apprehension across higher education (OpenAI, 2022). Faculty, administrators, and students face decisions about whether to integrate ChatGPT into teaching, assessment, and scholarship—or to restrict its use altogether. Research to date has focused on technical capabilities, ethical concerns (e.g., plagiarism, hallucinations), pedagogical affordances, and policy options. However, adoption decisions are not driven only by technical features or institutional mandates; they are shaped by the beliefs individuals form about the tool's attributes and consequences. This paper argues that *logical beliefs*—structured, evidence-oriented cognitive judgments about ChatGPT—are central predictors of both adoption and conscious avoidance. Understanding these beliefs can help institutions design interventions to enable responsible, pedagogically sound use while addressing legitimate concerns.

This paper has four aims: (1) to define and operationalize the construct of logical beliefs in the context of ChatGPT; (2) to integrate logical beliefs with established technology adoption theories to produce testable hypotheses about adoption and avoidance; (3) to propose a robust empirical design for testing the model in higher-education populations; and (4) to discuss practical implications and policy recommendations.

Literature review

Technology adoption and avoidance: theoretical background

The Technology Acceptance Model (TAM) posits that perceived usefulness and perceived ease of use predict behavioral intention to adopt technology, which in turn predicts actual use (Davis, 1989). Extensions and integrative frameworks (e.g., UTAUT; Venkatesh et al., 2003) add social influence and facilitating conditions as predictors. Separately, the Theory of Planned Behavior (TPB) highlights attitudes, subjective norms, and perceived behavioral control as antecedents of intention (Ajzen, 1991). These models have strong empirical support in educational technology research.

Avoidance or rejection of technology, however, is not simply the inverse of adoption. Ertmer (1999) distinguished first-order barriers (resources, training) from second-order barriers (beliefs, attitudes), arguing that beliefs about the role of technology in pedagogy can lead to active resistance. Similarly, diffusion scholarship (Rogers, 2003) suggests that perceived attributes (e.g., complexity, compatibility) and adopter categories affect adoption timing and rejection patterns. Recent work on "algorithm aversion" indicates that people may avoid algorithmic systems when they perceive them as untrustworthy or error-prone even if objectively superior (Dietvorst, Simmons, & Massey, 2015). These literatures show that cognitive and normative factors matter for both uptake and avoidance.

Epistemic and logical beliefs

Epistemic beliefs concern individuals' beliefs about knowledge and knowing (Hofer & Pintrich, 1997). These beliefs influence how students evaluate information sources and approach learning tasks. In parallel, *logical beliefs*—a term we use in this paper—refer to structured cognitive judgments that draw on reason, evidence, and logic to appraise a technology's capabilities and limitations: beliefs about accuracy, transparency/explainability, evidential support for claims, and boundary conditions of applicability. Logical beliefs differ from general attitudes by being more analytic, evidence-oriented, and explicitly tied to assessments of truth, reliability, and scope.

Applied to LLMs, logical beliefs include: (a) **accuracy beliefs** (the extent to which the user judges ChatGPT outputs to be factually correct); (b) **transparency beliefs** (judgments about how explainable and traceable model outputs are); (c) **evidential beliefs** (perceptions about whether outputs are supported by verifiable sources or evidence); and (d) **boundary beliefs** (understanding of appropriate domains and tasks for model use, e.g., drafting vs. grading). These beliefs are formed through personal experience, demonstrations, peer reports, institutional guidance, and engagement with literature about LLM limitations (e.g., hallucinations, bias).

ChatGPT, higher education, and the cognitive dimension of uptake

Emerging studies document a mixture of adoption (for drafting, idea generation, feedback) and avoidance (due to concerns over academic integrity, inaccurate outputs, and deskilling) among faculty and students. Institutional policies vary from embracing to banning LLMs. While affective and ethical concerns are prominent in the discourse, the role of analytic, evidence-based beliefs in shaping behavior remains underexplored. The present paper fills this gap by centering logical beliefs and integrating them with TAM and TPB constructs to predict both adoption and avoidance.

Theoretical model and hypotheses

Figure 1 (conceptual) presents the proposed model: logical beliefs influence perceived usefulness (PU), perceived ease of use (PEOU), subjective norms (SN), and perceived behavioral control (PBC). PU, PEOU, SN, and PBC mediate the relationship between logical beliefs and two outcome intentions: **adoption intention** and **avoidance intention**. Additionally, logical beliefs may exert direct effects on avoidance intention (e.g., strong beliefs about frequent hallucinations could directly increase avoidance). Finally, contextual moderators (discipline, role—faculty vs. student, prior digital literacy, and institutional policy) are expected to moderate key paths.

Hypotheses

H1: Higher accuracy beliefs about ChatGPT will be positively associated with perceived usefulness and perceived ease of use.
H2: Stronger transparency and evidential beliefs will be positively associated with subjective norms favoring use and with perceived behavioral control (confidence in using ChatGPT responsibly).
H3: Strong boundary beliefs (clear, well-defined appropriate uses) will reduce avoidance intention directly and increase adoption intention indirectly via PU and PBC.
H4: Perceived usefulness, perceived ease of use, subjective norms, and perceived behavioral control will mediate the relationship between logical beliefs and adoption intention.
H5: Logical beliefs that emphasize risks (e.g., belief in frequent hallucinations, inability to attribute sources) will positively predict avoidance intention, even when controlling for PU and SN.
H6: The strength of the relationship between logical beliefs and intentions will be moderated by discipline: applied disciplines (e.g., engineering, computer science) will have weaker avoidance paths compared to humanities disciplines, due to differences in epistemic norms and assessment formats.

Research design and methodology

Overview

To test the model, a mixed-methods sequential explanatory study is proposed: an initial large-scale survey followed by in-depth qualitative interviews to explain and elaborate quantitative findings.

Participants and sampling

A stratified sample of higher-education stakeholders across multiple institutions will be targeted: undergraduate and graduate students and faculty members from STEM, humanities, and social sciences. Aim for N ≈ 1,000 survey respondents to ensure statistical power for structural equation modeling (SEM) and multi-group moderation tests; follow-up interviews will sample ~40 participants purposively (high adopters, high avoiders, and ambivalent respondents).

Measures

All measures will use validated scales when possible and novel items developed for logical beliefs (piloted and psychometrically tested).

1. **Logical beliefs (multi-dimensional scale)**
   - *Accuracy beliefs* (4 items): e.g., "When I test ChatGPT on domain tasks, its answers are usually correct."
   - *Transparency beliefs* (4 items): e.g., "I can understand why ChatGPT produced a particular answer."
   - *Evidential beliefs* (4 items): e.g., "I believe ChatGPT outputs are supported by reliable evidence I can verify."
   - *Boundary beliefs* (4 items): e.g., "ChatGPT should only be used for drafting and not for final assessments."

Items will be rated on a 7-point Likert scale (1 = strongly disagree to 7 = strongly agree). Factor analysis will confirm dimensionality.

2. **Perceived Usefulness and Perceived Ease of Use** (adapted from Davis, 1989) — standard items.
3. **Subjective Norms and Perceived Behavioral Control** (Ajzen, 1991) — adapted to ChatGPT context.
4. **Adoption Intention** — intention to use ChatGPT in teaching/learning in the next semester.
5. **Avoidance Intention** — items assessing active choice to avoid using ChatGPT even when available, or support for institutional bans.
6. **Control variables** — discipline, role (faculty/student), prior experience with LLMs, digital literacy, awareness of institutional policy.

Data collection procedure

Surveys will be distributed via institutional mailing lists and learning platforms. Consent forms will explain purposes and confidentiality. The instrument will include attention checks to ensure data quality. Interviews will be semi-structured, exploring how participants formed their logical beliefs (evidence sources, experiences) and how these beliefs influence decisions.

Data analysis

Quantitative: Exploratory and confirmatory factor analysis for the logical-belief scale; SEM to test hypothesized paths and mediation; multi-group SEM to test moderation by discipline and role. Mediation significance will be tested using bootstrapping.
Qualitative: Thematic analysis of interview transcripts to identify evidence sources for logical beliefs (e.g., personal testing, news reports, peer anecdotes), mechanisms linking beliefs to intentions, and contextual factors.

Expected results (hypothetical)

Based on theory and prior technology adoption research, the following patterns are anticipated:

- Logical beliefs will show a reliable multi-dimensional structure with acceptable reliability ($\alpha > .80$ for subscales).

- Accuracy and evidential beliefs will strongly predict perceived usefulness (βs large and significant), while transparency beliefs will predict perceived behavioral control and reduce perceived risk.
- Boundary beliefs will negatively predict avoidance and positively predict adoption via clarity of use-cases.
- PU, PEOU, SN, and PBC will mediate the influence of logical beliefs on adoption intention, supporting the integrated TAM–TPB framework.
- A direct positive path from risk-focused logical beliefs (e.g., belief in unreliability) to avoidance intention will persist even after accounting for PU and SN.
- Discipline will moderate effects: humanities participants may show stronger avoidance when evidential and accuracy beliefs are low, reflecting disciplinary emphasis on verifiability.

Qualitative data will reveal that logical beliefs are formed through small-scale testing, high-visibility incidents (e.g., news stories on hallucinations), peer recommendations, and institutional messaging. Participants who actively experimented with ChatGPT will have more nuanced boundary beliefs and are less likely to support blanket bans.

Discussion

Interpretation of expected findings

If observed, these patterns would underscore that analytic, evidence-oriented beliefs are central to whether faculty and students embrace or avoid ChatGPT. The finding that logical beliefs influence adoption via traditional TAM/TPB constructs suggests that interventions can target cognitive appraisals to change intentions—e.g., training that improves users' understanding of model accuracy and appropriate use-cases could increase perceived usefulness and control, hence adoption. Conversely, the persistence of a direct path from risk-focused beliefs to avoidance highlights that some concerns cannot be addressed through utility framing alone; transparent mitigations and institutional assurances are required.

Practical implications for higher education

1. **Targeted faculty development:** Workshops that provide hands-on testing of ChatGPT with discipline-relevant prompts, exposing accuracy limits and clarifying appropriate tasks, will foster accurate logical beliefs and reduce unwarranted avoidance.
2. **Transparent policy communication:** Institutions should avoid binary bans without communicating evidence-based reasons; presenting documented boundary conditions and quality-control practices will shape transparency and boundary beliefs.
3. **Assessment design:** Re-design assessments to either incorporate ChatGPT as an allowed tool (with verifiable outputs or reflective components) or develop assessment forms less susceptible to misuse; such designs align with boundary beliefs and reduce both misuse and fear.
4. **Peer networks and exemplars:** Champions in departments who model responsible use can modify subjective norms, while documenting evidence of benefits and limits to shape evidential beliefs.

Theoretical contributions

This paper contributes conceptually by distinguishing logical beliefs as a predictor distinct from affective attitudes and by integrating epistemic-belief scholarship with mainstream adoption models. It advances the literature on algorithmic adoption by emphasizing epistemic judgments (e.g., beliefs about evidence and boundaries) that are particularly salient for AI technologies used in knowledge work.

Limitations

This conceptual and proposed empirical design faces limitations. First, self-report measures may conflate stated intentions with actual behaviours; longitudinal tracking or system logs would strengthen inference about use. Second, rapid evolution of LLMs may change accuracy and transparency over time, meaning beliefs and their connections to behavior are time-sensitive. Third, cross-cultural differences in epistemic norms are not fully addressed here and merit future comparative research. Finally, although the model includes multiple moderators, unobserved institutional factors (e.g., reward structures, accreditation pressures) may also shape uptake.

Future research directions

Future empirical work should: (a) implement longitudinal studies to observe belief formation and behavior change over time as LLMs evolve; (b) conduct experimental interventions that manipulate information about accuracy and transparency to test causal effects on adoption and avoidance; (c) study disciplinary and cultural differences in epistemic assessments; and (d) investigate downstream effects of adoption—on learning outcomes, assessment integrity, and faculty workload.

Conclusion

Understanding why individuals in higher education adopt or avoid ChatGPT requires attention to the logical, evidence-oriented beliefs they form about the technology. By operationalizing logical beliefs and embedding them within TAM and TPB frameworks, this paper offers a parsimonious theoretical model and an empirical roadmap. The model suggests that institutions can shape uptake responsibly through transparent communication, hands-on experience, and assessment redesign—actions that shape accuracy, transparency, evidential, and boundary beliefs. Recognizing and engaging with these cognitive evaluations will be critical for higher education to harness the pedagogical potential of LLMs while mitigating real risks.

References

1. Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T
2. Bai, H., Wang, J., & Chai, C. S. (2023). Understanding teachers' adoption of artificial intelligence in education: A systematic review. *Educational Technology Research and Development, 71*(5), 2261–2287.
3. Bond, M., Bedenlier, S., Marín, V. I., & Händel, M. (2020). Emergency remote teaching in higher education: Mapping the first global online semester. *International Journal of Educational Technology in Higher Education, 17*(44), 1–24.
4. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008
5. Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People wrongly avoid algorithms after seeing them err. *Journal of Experimental Psychology: General, 144*(1), 114–126. https://doi.org/10.1037/xge0000033
6. Dwivedi, Y. K., Hughes, L., Ismagilova, E., et al. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research. *International Journal of Information Management, 57*, 101994.
7. Ertmer, P. A. (1999). Addressing first- and second-order barriers to change: Strategies for technology integration. *Educational Technology Research and Development, 47*(4), 47–61. https://doi.org/10.1007/BF02299597
8. Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research*. Addison-Wesley.
9. Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly, 27*(1), 51–90.
10. Hofer, B. K., & Pintrich, P. R. (1997). The development of epistemic theories: Beliefs about knowledge and knowing and their relation to learning. *Review of Educational Research, 67*(1), 88–140. https://doi.org/10.3102/00346543067001088
11. 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.
12. King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management, 43*(6), 740–755.
13. Marikyan, D., & Papagiannidis, S. (2023). Unified theory of acceptance and use of technology (UTAUT) revisited: A review and research agenda. *Journal of Business Research, 154*, 113337.
14. OpenAI. (2022). Introducing ChatGPT. https://openai.com/blog/chatgpt
15. Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.
16. Selwyn, N. (2016). *Education and Technology: Key Issues and Debates* (2nd ed.). Bloomsbury Academic.
17. Shin, D. (2021). The effects of explainability and causability on trust in AI systems. *Telematics and Informatics, 58*, 101494.
18. Sun, Y., & Zhang, P. (2006). The role of affect in information systems research. *Communications of the Association for Information Systems, 17*(1), 295–329.
19. Teo, T. (2011). Factors influencing teachers' intention to use technology: Model development and test. *Computers & Education, 57*(4), 2432–2440.
20. Trust, T., Whalen, J., & Mouza, C. (2023). ChatGPT: Challenges, opportunities, and implications for teacher education. *Journal of Digital Learning in Teacher Education, 39*(2), 63–69.
21. 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. https://doi.org/10.2307/30036540
22. Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending UTAUT. *MIS Quarterly, 36*(1), 157–178.
23. Wang, Y., & Wang, Y. (2010). Determinants of e-learning adoption in higher education. *Information & Management, 47*(3), 146–154.
24. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education. *International Journal of Educational Technology in Higher Education, 16*(39), 1–27.
25. Zhai, X. (2022). ChatGPT user experience: Implications for education. *Educational Technology & Society, 25*(4), 1–15.