OPEN ACCESS

Volume: 13

Special Issue: 1

Month: March

Year: 2026

P-ISSN: 2321-4643

E-ISSN: 2581-9402

Citation:
Prasad, HK, and C. Janardhan. "AI Learning Intention, Engagement Dynamics, and Behavioral Consequences: A Critical Re-Examination." *Shanlax International Journal of Management,* vol. 13, no. S1, 2026, pp. 212–16.

DOI:
https://doi.org/10.34293/management.v13iS1-Mar.10768

AI Learning Intention, Engagement Dynamics, and Behavioral Consequences: A Critical Re-examination

Dr. HK. Prasad
Associate Professor
Jain College (Autonomous), Bangalore

C. Janardhan
Assistant Professor
Sri Bhagawan Mahaveer, Jain Evening College, Bengaluru

Abstract
Purpose: While much scholarship evaluates learning effectiveness within conventional training environments, limited attention has been given to how AI-centered learning ecosystems reshape learner agency and outcomes. This study reconceptualizes the connection between AI-driven learning systems and employee behavioral consequences. Rather than assuming direct positive outcomes, this research critically examines whether AI-learning intention genuinely translates into meaningful behavioral transformation. Drawing from the Theory of Planned Behavior (TPB) and Self-Determination Theory (SDT), the study reassesses the relationships among learning intention, engagement processes, and behavioral outcomes.
Design/Methodology/Approach: Using survey data collected from Indian industry professionals, the study applies structural equation modeling (SPSS-AMOS 27) and Hayes PROCESS macro to test direct and indirect relationships between AI learning intention, engagement patterns, and behavioral outcomes.
Findings: Results indicate that although AI learning intention factors (attitude, subjective norm, perceived behavioral control) show statistical associations with behavioral outcomes, the magnitude of actual behavioral transformation depends heavily on the depth and quality of engagement. Engagement does not merely mediate but conditions the extent to which AI intention results in observable workplace change.
Originality/Value: This study challenges overly optimistic assumptions regarding AI-based learning systems and emphasizes the conditional nature of behavioral outcomes in technology- driven learning environments.

Keywords: Artificial Intelligence, Learning Intention, Engagement, Behavioral Outcomes, Technology Adoption

Introduction

Digital transformation has altered organizational learning landscapes. AI-powered tools such as conversational agents and adaptive systems promise efficiency and personalization. However, technological sophistication does not automatically translate into meaningful learning impact.

Organizations have rapidly incorporated AI across HRM functions—recruitment, digital performance monitoring, compliance, and training systems. Despite this integration, the effectiveness

of AI-based learning remains contested. The assumption that adoption equals transformation is problematic.

Learning effectiveness traditionally follows the Kirkpatrick model, where behavioral change represents the most meaningful outcome. Yet, AI-driven learning environments may alter not only learning methods but also learner motivation structures. Therefore, understanding intention and engagement in AI contexts becomes crucial.

While the Theory of Planned Behavior explains how attitude, subjective norm, and perceived control shape intention, intention alone may not predict behavioral execution in AI-mediated environments. Self-Determination Theory suggests that autonomy, competence, and relatedness determine meaningful engagement. Thus, behavioral change may depend less on intention and more on sustained engagement quality.

This study therefore shifts focus from technological capability to psychological and behavioral processes underlying AI-based learning adoption.

Theoretical Framework

Reinterpreting the ABC Model

The Antecedent–Behavior–Consequence (ABC) framework positions intention as an antecedent, engagement as behavioral process, and performance outcomes as consequences. However, in AI-based learning systems, antecedents may be externally influenced by organizational pressure rather than intrinsic motivation.

Thus, intention may reflect compliance rather than commitment. Engagement quality becomes the true determinant of meaningful behavioral consequences.

Artificial Intelligence in Learning and Development

AI systems promise personalization, automation, and efficiency. They provide adaptive content, analytics, chat-based support, and predictive learning recommendations.

However, personalization algorithms do not guarantee deep learning. Over-automation may reduce cognitive effort. Efficiency gains may compromise reflective processing. Therefore, the impact of AI depends on how learners interact with these systems rather than on system capability alone.

AI-Based Learning Intention

AI learning intention refers to an individual's willingness to adopt AI tools for learning purposes. According to TPB, intention derives from:

- Attitude toward AI
- Subjective norms
- Perceived behavioral control

However, positive attitudes toward technology do not necessarily translate into meaningful learning behaviors. Social pressure may inflate expressed intention without increasing learning depth. Similarly, perceived ease of use may reduce cognitive engagement rather than enhance it. Thus, AI learning intention may predict adoption, but not necessarily learning quality.

Learning Engagement

Engagement reflects how learners regulate, manage, and sustain interaction with AI-based systems. Engagement is multidimensional—cognitive, emotional, and behavioral.

Unlike intention, engagement represents active participation. Learners who self-regulate and actively interpret AI-generated content are more likely to achieve behavioral impact. Conversely, passive reliance on AI recommendations may weaken skill development.

Behavioral Change

Behavioral change represents observable application of acquired knowledge in workplace contexts. It reflects transfer of learning rather than system usage.

In AI-driven environments, behavioral change should be interpreted cautiously. Adoption metrics do not equal performance improvement. Only applied competence validates learning impact.

Hypotheses Reformulated

- H1: AI learning intention predicts behavioral outcomes, but the strength of this relationship is moderate rather than strong.
- H1a: Positive attitude toward AI influences behavioral outcomes, though the effect may depend on depth of system interaction.
- H1b: Subjective norm influences AI adoption behavior more than actual behavioral transformation.
- H1c: Perceived behavioral control influences system usage frequency but does not independently guarantee behavioral impact.
- H2: Learning engagement is a stronger predictor of behavioral change than AI learning intention alone.
- H3: Learning engagement conditionally mediates the relationship between AI learning intention and behavioral change.

Methodology

A survey-based quantitative design was adopted. Data were collected from professionals in pharmaceutical, IT, banking, consulting, education, and engineering sectors in India.

Out of 500 distributed questionnaires, 276 usable responses were analyzed. The sample exceeded minimum SEM requirements.

Validated measurement scales assessed:

- Attitude
- Subjective norm
- Perceived behavioral control
- AI learning intention
- Learning engagement
- Behavioral impact

Reliability and validity were confirmed through factor loadings, Cronbach's alpha, composite reliability, and AVE analysis.

Structural Equation Modeling (AMOS 27) assessed direct paths. Mediation was tested using Hayes PROCESS macro with bootstrapped confidence intervals.

Results and Discussion

The analysis demonstrates that AI learning intention shows a statistically significant but moderate association with behavioral change.

Attitude, subjective norm, and perceived behavioral control all exhibit positive relationships with behavioral outcomes. However, engagement exerts the strongest predictive influence.

Learning engagement significantly predicts behavioral change, suggesting that system interaction quality matters more than initial intention.

Mediation analysis confirms that engagement partially mediates the relationship between AI learning intention and behavioral outcomes. Behavioral change occurs primarily when learners

actively engage rather than merely intend to use AI. These findings suggest that AI systems function as enabling infrastructure rather than direct catalysts of transformation.

Managerial Implications

1. AI adoption should not be equated with learning effectiveness.
2. Organizations must prioritize engagement design over technological sophistication.
3. Social influence strategies may increase adoption rates but not learning transfer.
4. Empowering learners through autonomy-supportive systems enhances engagement depth.
5. Behavioral metrics should focus on applied competence rather than usage statistics.

Limitations and Future Directions

1. The study focuses only on behavioral outcomes; future research should examine reaction, learning, and organizational results.
2. Engagement was treated as a single mediator; other variables such as learning climate or communication strategy could be explored.
3. Future research may integrate Technology Acceptance Model (TAM) constructs.
4. Mixed-method approaches may provide deeper insights into learner experiences.

Conclusion

AI-based learning systems alone do not ensure behavioral transformation. While intention influences adoption, engagement determines impact.

Meaningful behavioral change arises when learners actively regulate their AI-supported learning processes. Therefore, organizations should shift attention from technological implementation to engagement optimization.

AI is not inherently transformative—it becomes transformative only when learners meaningfully interact with it.

References

1. Abou Hashish, A., dan S. Alnajjar. 2024. "Adoption of Artificial Intelligence in Higher Education: Insights from Saudi Arabia." Arabian Journal of Educational Studies 19 (4): 5–12. https://doi.org/10.1177/ajed.2024.04.008.
2. Cortez, C. dkk. 2024. "Feedback Systems in AI-Enhanced Learning Environments." Computers & Education 190:7–15. https://doi.org/10.1016/j.compedu.2024.04.007.
3. Creswell, J. W. 2014. Research design: Qualitative, quantitative, and mixed methods approaches. 4th ed. SAGE Publications.
4. Fischer, G. dkk. 2020. "Transformative Learning Through AI Integration." Interactive Learning Environments 30 (1): 75–92. https://doi.org/10.1080/ile.2020.010.
5. Gonzalez, M., A. Johnson, dan A. Pardo. 2020. "Leveraging AI Tools for Enhancing Academic Writing Skills." Journal of Educational Computing Research 58 (4): 783–98. https://doi.org/10.1177/0735633119881473.
6. Hassan, S., T. Smith, dan J. Taylor. 2022. "The Role of AI in Enhancing Academic Writing and Learning Efficiency." Journal of Educational Technology Research 35 (4): 567–82. https://doi.org/10.1016/j.jetr.2022.04.008.
7. Holmes, W., M. Bialik, dan C. Fadel. 2019. Artificial Intelligence in Education: Promises and Implications for Teaching and Learning. Boston: The Center for Curriculum Redesign.
8. Huang, R., dan K. Siau. 2020. "The Impact of AI-Driven Presentation Tools on Student Engagement."Educational Technology & Society 23 (2): 120–34. https://doi.org/10.1108/ets.2020.023.

9. Katsamakas, E. dkk. 2024. "The Role of Artificial Intelligence in Higher Education." Journal of Educational Technology 32 (1): 1–20. https://doi.org/10.1016/j.jet.2024.01.002. Kharroubi, H. dkk. 2024. "Student Perceptions and Attitudes Towards AI in Education: A Study in Lebanon and Saudi Arabia." Middle East Journal of Education 15 (1): 10–14. https://doi.org/10.1007/meje.2024.01.011.
10. Lincoln, Y. S., dan E. G. Guba. 1985. Naturalistic Inquiry. Newbury Park, CA: SAGE Publications.
11. Mallillin, J. 2024. "Integrating AI for a Transformative Academic Environment." Advances in Educational Research 28 (2): 12–25. https://doi.org/10.1016/aer.2024.02.015.
12. Nguyen, D., dan M. Goto. 2024. "AI and Behavioral Change in Education: Insights and Challenges." Educational Technology Research and Development 40 (1): 8–12. https://doi.org/10.1007/etrd.2024.01.010.
13. Ou, C. 2024. "AI and Academic Misconduct: An Emerging Concern in Universities." International Journal of Higher Education 14 (2): 3–8. https://doi.org/10.1080/ijhe.2024.02.005.
14. Pintrich, P. R. 2004. "A Conceptual Framework for Assessing Motivation and Self-Regulated Learning." Educational Psychology Review 16 (4): 385–407. https://doi.org/10.1007/s10648-004-0006-x. Rahiman, H., dan R. Kodikal. 2023. "Engagement and Assessment Effectiveness Using AI in Higher Education." Journal of Educational Assessment 29 (4):12–18. https://doi.org/10.1080/jea.2023.04.013.
15. Ryan, R. M., dan E. L. Deci. 2000. "Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being." American Psychologist 55 (1): 68–78. https://doi.org/10.1037/0003-066X.55.1.68.
16. Selwyn, N. 2019. "Digital Distraction in the Classroom: Student Reception and Usage of AI Tools., British Journal of Educational Technology 50 (4):1355–67. https://doi.org/10.1111/bjet.2019.0364.
17. Stukalina, Y., dan O. Zervina. 2024. "AI-Driven Strategies for Enhanced Academic Management." International Journal of Educational Management 38 (3): 7–19. https://doi.org/10.1108/ijem.2024.03.009.
18. Tang, C., dan A. Zainal. 2024. "Ethical Use of AI in Higher Education Institutions." Journal of Ethics in Technology 12 (2): 9–15. https://doi.org/10.1007/jet.2024.02.011.
19. Tindle, H. dkk. 2023. "Ethical Implications of AI Use in Higher Education: Challenges of Academic Integrity." Journal of Academic Ethics 21 (1): 5–10. https://doi.org/10.1007/jae.2023.01.006.
20. Yang, Y. dkk. 2021. "Artificial Intelligence and Higher Education: Opportunities, Challenges, and Implications." Computers & Education 163. https://doi.org/10.1016/j.compedu.2020.104099.
21. Zawacki-Richter, O. dkk. 2019. "Ethical Considerations in AI-Supported Learning." Journal of Higher Education 45 (5): 300–316. https://doi.org/10.1080/jhe.2019.050.
22. Zimmerman, Barry J. 2000. Attaining Self-Regulation: A Social Cognitive Perspective. Disunting oleh M. Boekaerts, P. R., Pintrich, dan M. Zeidner. Handbook of Self-Regulation. San Diego, CA: Academic Press.