2026 ASEE ANNUAL CONFERENCE June 21–24, 2026 | Charlotte Convention Center, NC

Host Sponsor UNC Charlotte

Paper ID #53081

Faculty Experiences with Emerging Technologies: A Case Study of Artificial Intelligence

Deborah Moyaki, University of Georgia

Deborah Moyaki is a doctoral student in the Engineering Education and Transformative Practice program at the University of Georgia. She holds a bachelor's degree in Educational Technology and is excited about the possibilities technology offers to the learning experience beyond the formal classroom setting. Her research focuses on improving the educational experience of engineering students using virtual reality labs and other emerging technologies.

Dr. Nathaniel Hunsu, The University of Georgia

Nathaniel Hunsu is an assistant professor of Engineering Education. He is affiliated with the Engineering Education Transformational Institute and the school of electrical and computer engineering at the university. His interest is at the nexus of the res

VINCENT OLUWASETO FAKIYESI, University of Georgia

Vincent Oluwaseto Fakiyesi is a doctoral student in the Engineering Education program at the University of Georgia. He holds a bachelor's degree in Chemical Engineering and is interested in advancing assessment practices to better understand student learning. His research focuses on cognitive diagnostic modeling, student misconceptions, and adaptive assessment systems. He applies diagnostic models to analyze large-scale educational assessment data and generate actionable insights that support teaching, learning, and personalized feedback in engineering education. He also examines assessment practices in the era of generative artificial intelligence, emphasizing adaptive, interpretable, and learning-centered systems.

Faculty Experiences with Emerging Technologies: A Case Study of Artificial Intelligence

Background

Although Artificial Intelligence (AI) has existed for several decades, the recent introduction and rapid adoption of generative AI (GenAI) tools in educational contexts have renewed attention to its instructional potential [1]. In engineering education, AI has been shown to support personalized learning and facilitate engagement with abstract and complex concepts, in turn preparing students for engineering practice. AI-driven chatbots support self-directed learning by assisting with knowledge acquisition, goal-directed practice, and knowledge activation, core components of effective learning processes [2]. For instance, Bachiri et al. [3] developed an AI-based educational model to address the demand for assessment content in online courses while reducing the cost and labor associated with manual question generation. Similarly, Kavianpour [4] explored the integration of AI tools such as ChatGPT in first-year programming courses, with improvements in student engagement, conceptual understanding, and exam performance reported. Their findings suggest that GenAI tools can serve as effective instructional supports when integrated into coursework. Collectively, these studies illustrate the growing potential of AI to enhance learning and support faculty instructional practices, thereby improving student learning outcomes.

Within engineering education, however, research on emerging technology adoption is largely oriented toward evaluating learning outcomes rather than examining the adoption process itself. A smaller subset of studies focuses on identifying factors that influence adoption, often drawing on predictive models such as the Technology Acceptance Model (TAM). For instance, Wang et al. [5] sought to test a TAM-based research model to identify factors influencing faculty acceptance of AI, while Abulail et al. [6] examined organizational and institutional factors that prompt higher education institutions to adopt AI technologies. Although such studies offer a useful overview of variables associated with acceptance, they tend to conceptualize adoption as a static outcome rather than as a dynamic process shaped by evolving faculty experiences. Faculty serve as gatekeepers who determine whether, how, and for what purposes AI tools are introduced into instructional contexts. Recent scholarship suggests that faculty perceptions, concerns, and decision-making processes related to technology use are dynamic and context-dependent [7]. Scherer et al. [8] argue that the meaningful inclusion of technology in learning environments requires attention to technology acceptance, yet much of the existing work remains focused on identifying predefined factors that influence acceptance rather than understanding how faculty navigate adoption over time. This emphasis risks positioning faculty within narrowly defined models that leave limited room to examine the broader, socially constructed processes through which technologies such as AI are interpreted, adapted, and integrated into teaching practice.

A small but growing body of work has begun to address this gap by centering faculty perspectives in studies of emerging technology adoption. For example, Jarvie-Eggart et al. [9] examined faculty adoption of engineering technologies by moving beyond existing adoption models to identify factors that faculty themselves considered relevant to their adoption experiences. Their work highlights the socially constructed nature of technology use and positions faculty, not the technology, as the central focus of adoption. This perspective contrasts with prior model-testing approaches by enabling a more holistic understanding of adoption that extends beyond predefined variables, particularly given AI's disruptive, rapidly evolving nature. Similarly, Simelane et al. [10] explored faculty perceptions of AI use in the curriculum using a qualitative approach that foregrounded faculty voice rather than relying solely on predictive adoption models. Their findings revealed faculty rationales for using AI, concerns about the lack of clear guidelines, and calls for responsible, ethical AI use, insights that are difficult to capture through technocentric or factor-driven approaches alone. While technology adoption models remain valuable for providing high-level insights into adoption patterns, developing effective faculty development supports requires a deeper understanding of how faculty experience AI adoption in practice.

Taken together, the existing literature points to the need for research examining AI adoption as a process shaped by faculty beliefs, experiences, and contextual realities. By centering faculty voice and viewing adoption as dynamic rather than outcome-driven, such work can offer critical insights for designing faculty development initiatives that support purposeful, adaptable, and responsible integration of AI in engineering education. Therefore, the purpose of our study is to explore how engineering faculty experience adopting AI tools to foster student competencies. Specifically, we ask the following research question: **How do influencing factors for faculty adoption of AI align with existing technology adoption frameworks?**

Conceptual Framework

Applying a single technology adoption model to examine faculty integration of AI in engineering education presents limitations. AI adoption in academic contexts extends beyond mere acceptance to encompass instructional practices, pedagogical goals, disciplinary norms, and faculty beliefs about student learning and career preparation. Prior research has noted that emerging technologies, particularly AI, interact with multiple dimensions of educational systems, making single-theory approaches insufficient for capturing adoption dynamics in higher education [11]. To address this complexity, this study integrates three complementary theoretical perspectives: the Technology Acceptance Model (TAM), Diffusion of Innovation (DOI), and Social Cognitive Career Theory (SCCT).

TAM conceptualizes technology adoption as a function of individuals' cognitive beliefs, particularly perceived usefulness and perceived ease of use, which shape attitudes and behavioral intentions toward technology use [12]. In educational contexts, TAM has been widely applied to examine faculty acceptance of educational technologies, including AI, and provides a robust lens for understanding how faculty evaluate technologies during early stages of adoption [8]. However, TAM largely treats adoption as an individual cognitive process and provides limited insight into social influence, institutional context, or the broader purposes guiding technology use.

DOI complements TAM by emphasizing the role of social systems, communication channels, and innovation characteristics, such as relative advantage, compatibility, and observability, in shaping how technologies spread over time [13]. Within higher education, DOI has been used to explain how institutional culture, peer influence, and disciplinary norms affect faculty adoption of instructional innovations [14]. While DOI captures important social and contextual influences on diffusion, it places less emphasis on individual motivation and does not explicitly address how sustained technology use connects to longer-term educational or professional outcomes. Although integrating TAM and DOI offers a more comprehensive understanding of adoption by combining cognitive and social dimensions, this integration remains largely descriptive of adoption mechanics. Prior studies combining these models have primarily focused on identifying factors influencing acceptance and use, rather than on how adoption aligns with broader educational purposes such as competency development and career readiness [11,14]. As a result, adoption is often conceptualized as a discrete outcome rather than as an evolving, purpose-driven process.

To address this limitation, this study incorporates SCCT, which emphasizes self-efficacy, outcome expectations, and goal-setting as key mechanisms driving sustained engagement and development [15]. SCCT has been widely applied in engineering education to understand students' and educators' beliefs about competence, persistence, and career preparation [16]. Integrating SCCT into technology adoption research enables examination of how faculty perceptions of AI influence not only their instructional practices but also their beliefs about students' skill development and professional readiness.

By integrating TAM, DOI, and SCCT into a single conceptual framework, this study addresses key limitations of each theory when applied independently. TAM explains faculty cognitive beliefs that shape initial adoption intentions, DOI captures the social and institutional contexts that influence diffusion and sustained use, and SCCT links adoption experiences to motivational processes and long-term educational goals. Together, these frameworks enable a process-oriented understanding of AI adoption that centers faculty agency and connects technology use to student competency development. Figure 1 provides a graphical representation of the conceptual framework.

To date, no empirical study has integrated TAM, DOI, and SCCT to examine faculty adoption of AI within engineering education. This integrated framework provides a theoretically grounded foundation for investigating how internal beliefs, external contexts, and purpose-driven motivations interact to shape faculty experiences with AI adoption. In doing so, it advances adoption research beyond technocentric and outcome-focused models toward a holistic understanding of how faculty navigate emerging technologies in support of meaningful learning and professional preparation.

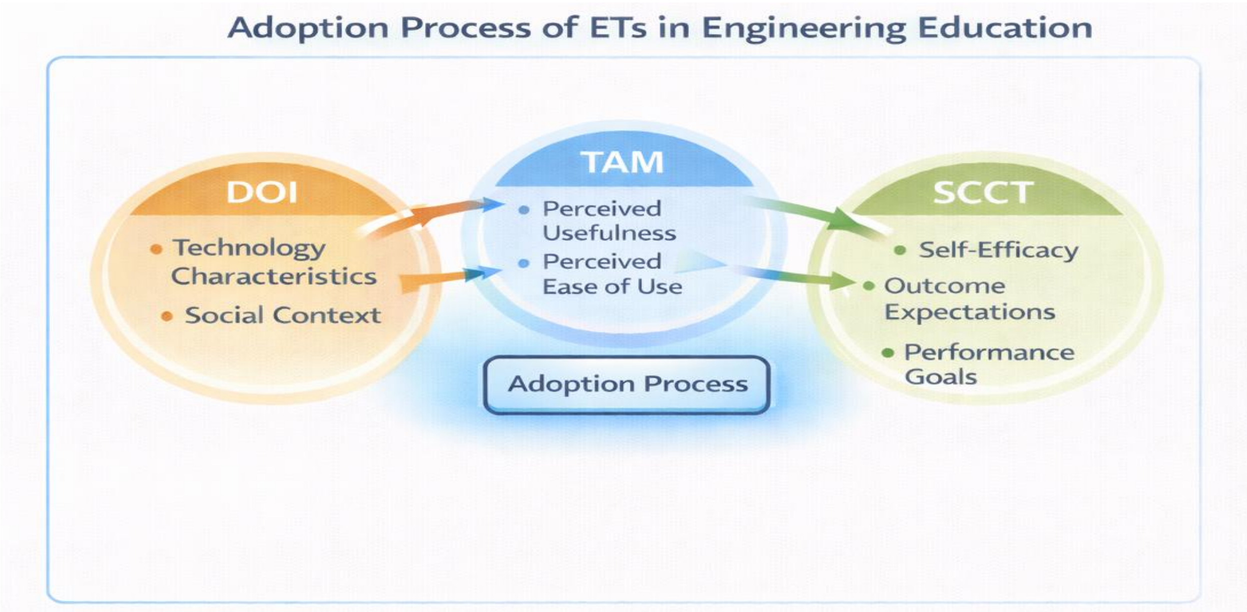

Figure 1: Conceptual Framework

Methodology

This study employed a deductive qualitative approach informed by the integrated conceptual framework. The purpose of the deductive analysis was to examine the extent to which the framework captured key aspects of faculty members' experiences with adopting AI in engineering education. Rather than testing the framework in a predictive sense, the analysis sought to explore how well the theoretical constructs aligned with and illuminated faculty members' experiences of adopting AI in engineering education for student competency development.

Participants

Three engineering faculty members across two R1 public institutions in the United States were interviewed about their emerging technology adoption process. For each interview, participants anchored their reflections in one primary engineering course in which they had implemented AI. The instructional focus of these courses shaped how AI was integrated and how faculty described their adoption experiences. Table 1 provides a breakdown of the demographics of faculty participants in our study.

Table 1: Faculty Participant Demographics

Pseudo Name	Gender Identity	Academic Discipline	Teaching Experience	Course Referenced
Dr. G	Man	Structural Engineering	6 to 10 years	Structural Design
Dr. T	Woman	Environmental Engineering	6 to 10 years	Engineering Fundamentals
Dr. D	Man	Electrical Engineering	11 to 15 years	Electronics

Data Collection
An interview protocol was developed based on the integrated conceptual framework. Faculty participants were recruited through professional networks via targeted recruitment emails. An initial screening survey was administered to identify faculty who had implemented AI within a specific engineering course, which served as the primary inclusion criterion. Semi-structured interviews were conducted via Zoom or in person, depending on the participant's preference, and lasted approximately 45 minutes on average.

Data Analysis
A codebook was developed based on the integrated conceptual framework. Interviews were transcribed using TurboScribe. Each transcript was subsequently reviewed while listening to the original audio recording to verify accuracy and correct transcription errors. This validation process also served as an initial stage of data familiarization prior to coding. Interview transcripts were imported into NVivo, a qualitative analysis software, to support the coding process. Deductive codes derived from the codebook were applied to the transcripts and mapped to relevant segments of the data.

We employed a deductive, theory-driven coding approach guided by the integrated conceptual framework. Coding was conducted by the first author using a predefined codebook in which each deductive code was clearly defined based on constructs from TAM, DOI, and SCCT. Throughout the coding process, the coder consistently referred back to the code definitions to ensure alignment between theoretical constructs and data segments. Within each theory, we identified instances in which participants' narratives reflected relevant constructs and examined how these constructs were expressed in practice. Results are organized by theoretical lens to illustrate how different aspects of the adoption process were captured across frameworks. We also include exemplar quotes that capture each code within the conceptual framework.

Results

Technology Acceptance Model (TAM)

Perceived Ease of Use
Perceived ease of use emerged across all three faculty members' adoption experiences, though it manifested in distinct ways. For one faculty member, ease of use was primarily associated with the accessibility and intuitive nature of AI tools, which initially motivated the decision to introduce AI as a learning support for students. For another faculty member, perceptions of ease of use were shaped through exposure to AI during a professional development workshop, where facilitators demonstrated seamless implementation in instructional contexts. However, this faculty member later reflected that translating those demonstrations into actual classroom practice required substantially more effort than initially anticipated. Although the perceived simplicity of AI tools initially attracted this faculty member, the realities of pedagogical integration revealed additional instructional and logistical demands.

For the third faculty member, perceived ease of use was associated with a low barrier to experimentation. The ability to quickly try AI tools and observe successful outputs encouraged early exploration and reduced hesitation about adoption. Across participants, perceived ease of use served as an entry point into adoption, but faculty experiences revealed that ease of initial interaction did not necessarily translate into ease of instructional integration.

"It's because it's maybe ease of use in terms of accessibility, right? Like it's so accessible that it's like telling my students not to breathe air. You know, it's just, it's everywhere, right? Like you couldn't tell someone not to use their smartphone. Right?
That doesn't make any sense, especially when the faculty are using it. So, it's not so much it's ease of use, it's just that it's everywhere. I guess maybe that's part of its ease, is that it's easy access."

Perceived Usefulness

Perceived usefulness was a prominent and consistent factor across all three faculty members. However, faculty members identified usefulness through different instructional challenges and personal experiences. One faculty member expressed concern that students had not yet recognized the full potential of AI for supporting their learning. Having experienced the benefits of AI in their professional work, this faculty member was motivated to introduce AI to students, hoping they would discover similar value in their learning.

Another faculty member found AI tools useful during end-of-semester grading, where AI tools helped surface student misconceptions that might otherwise have gone unnoticed. This experience highlighted AI's potential as a supplemental tutoring resource capable of addressing learning gaps beyond what instructors could identify in real time. Continued experimentation further revealed AI's usefulness, reinforcing this faculty member's decision to introduce it as a personalized learning aid for students. Importantly, this faculty member framed AI not as a definitive solution to student learning challenges, but as an additional option that students could choose to engage with based on their needs.

A similar perspective was echoed by a third faculty member, who emphasized the importance of students recognizing AI's potential without becoming overly reliant on it or dismissing it entirely. This faculty member highlighted the breadth of possibilities offered by AI as a reason for sustained personal exploration prior to classroom implementation. Across participants, faculty described investing personal time to understand the instructional value of AI before formally introducing it to students, underscoring that perceived usefulness was often developed through iterative experimentation rather than immediate recognition.

"I think the tipping point was my own use, right? In reality, I started using it myself because I'm like, what is this? Let's figure it out. And then the more I started using it, the more I'm like, oh, this is really useful. Yeah, initially, and I still sometimes worry that they won't see the potential for it to assist them because there is some new, there are some new studies coming out saying, I don't know if you've read, there were studies years ago that talked about people who read online weren't doing as deep reading and as deep thinking as people who read paper books, right?"

Diffusion of Innovation (DOI)

Within the DOI framework, three innovation characteristics - complexity, observability, and trialability - were prominent across faculty adoption experiences, with these aspects most strongly articulated by Dr. T. Complexity was not associated with difficulty in operating AI tools themselves, as faculty generally perceived AI interfaces as accessible and easy to use. Instead, complexity emerged from uncertainty surrounding effective pedagogical implementation. Faculty described challenges related to the lack of clear expertise or established norms for using

AI to support student learning, noting that the “ready-to-use” nature of AI tools for anyone, regardless of instructional expertise, complicated decisions about responsible and effective integration.

Observability also played a meaningful role in adoption, as faculty encountered AI’s potential through colleagues’ use, professional settings, and personal exploration, as well as through the ease with which AI could be demonstrated directly to students. The visibility of AI’s capabilities, combined with minimal barriers to showing students how to engage with the tools, supported faculty willingness to explore adoption. Trialability further reinforced this process, as all faculty emphasized the importance of experimenting with AI personally before introducing it into their courses. The ability to test AI tools independently allowed faculty to assess their potential value for student learning and to inform decisions to extend their use beyond personal contexts.

At the same time, faculty identified tensions associated with diffusion, particularly around student perceptions of AI. One faculty member noted student concerns about whether AI could function as a legitimate learning tool rather than being synonymous with cheating, highlighting a disconnect between established academic norms and emerging instructional practices. Another faculty member framed AI as analogous to earlier information technologies, such as card catalogs prior to the internet, emphasizing its relative advantage as a tool for enhancing learning rather than undermining it. Together, these findings suggest that faculty adoption of AI is shaped not only by opportunities for experimentation and visibility but also by ongoing negotiation of complexity and compatibility within existing educational norms.

“Because everything is unknown. I think that's the biggest challenge. I don't know what is correct, what is incorrect, what is good, what is bad. Everyone is trying. I think so far that's the uncertainty. That's the challenge.”

“So the hype of implementations of generative AI has been kind of like sounding more and more in education. So that I decided to give it a try. And I remember that I mentioned it to the student. I think it's more just exploration. I'll say that the approach is not a systematic way, it's more like a brute force at first. So it started from a brute force first, right? Kind of like trial and error, see some promises, getting some workshops to help me become more aware of what can be done and maybe raise awareness among myself and to me”

Social Cognitive Career Theory (SCCT)

Within this theory, faculty experiences are manifested in different ways across the components of the SCCT performance model.

Outcome Expectations

Outcome expectations capture what faculty anticipated would result from students’ use of AI for learning. Faculty reported expectations for critical thinking, problem-solving, increased cognitive engagement, and improved learning strategies. All faculty highlighted awareness as a key expected outcome, describing it as students’ understanding of AI as a tool and its potential utility for their learning. Faculty expressed concern that students should be aware of both the benefits and limitations of AI, rather than underutilizing or avoiding it altogether, which motivated the formal introduction of AI into coursework rather than limiting exposure to informal suggestions.

Across participants, faculty noted a general lack of AI literacy among students despite its growing importance in the current educational and professional landscape, and viewed increased literacy as an important outcome of integrating AI into their courses. Two of the faculty members expected that using AI for learning would prompt deeper thinking, based on the belief that effective use requires students to critically evaluate and verify the information generated. These faculty members intended that, by mandating AI use in a course, students would gradually choose to incorporate it into their learning practices. At the same time, one faculty member expressed uncertainty about expected outcomes, noting concern that despite AI's observed potential, students might engage with the tool without deriving meaningful learning benefits due to the faculty member's own uncertainty.

Performance Attainment

Two faculty members' experiences aligned with the performance attainment component of SCCT. One faculty member reiterated concern that uncertainty surrounding AI's educational impact limited their ability to define concrete attainment levels for students. In contrast, another faculty member referenced industry reports and job postings that increasingly emphasize AI literacy, viewing this trend as justification for clearer attainment expectations. This faculty member hoped that student engagement with AI in the course curriculum would move beyond basic awareness toward effective and confident use, thereby better preparing students for industry and enhancing their competitiveness in the workforce.

Performance Goals

Faculty purposes for using AI in student learning varied widely and included increasing engagement, supporting personalized learning, addressing student needs, facilitating information-seeking, enabling the real-world application of abstract concepts, and equipping students with advanced skills. These purposes were evident across faculty members, with little overlap in individual performance goals. For example, one faculty member aimed to use AI to connect abstract course concepts to real-world applications, while another introduced AI in response to observed student exam challenges, with the intent of using it as a tutoring tool within the course curriculum. Another faculty member, influenced by changes in the professional landscape, expressed a desire to move beyond foundational skills that may be less relevant in emerging contexts and sought ways for students to use AI to acquire more advanced, future-oriented competencies.

"So when I was growing up, I was in eighth grade and I was in algebra. And I remember asking my algebra teacher in eighth grade to teach me how to do square roots by hand. And because there's a long way of doing it, just like there's a long way of doing division. And he's like, you're never gonna need to know these in your lifetime. There's a calculator. And I remember being so mad that someone knew how to do something and he wouldn't teach it to me. But what I found is like in my lifetime, my ability to understand how a logarithm is calculated or how a square root is calculated has not at all impacted my ability to be a good engineer, right? So I think the same thing is gonna happen is like what we expect our foundational skills, like you have to program. Maybe you don't have to program. You just have to know how to test a program to see is it doing what you want it to do?"

“last semester, when some students came to my office hour to discuss with me about mistakes in their exam, I asked the student to explain her work. And the explanation is not correct. We don't hope students only use AI to search for answers for the homework. They need to think about whether AI is providing valuable suggestions or information. That's why my initial guess is AI could be a tutor. Tutor means there is something I don't understand. Please explain to me. And then when I do something, my tutor will tell me, oh, here is wrong. This mistake probably means you have some misunderstanding in that OHMS law maybe or in somewhere else. So I have a chance to consider and then fix it. Yeah, so basically it's just more communication. I can seek help or seek feedback from my tutor.”

Discussion

Our findings regarding perceived ease of use (PEU) both align with and extend prior research on faculty adoption of emerging technologies. In contrast to Simelane et al. [10], who did not observe ease of use as a salient factor in faculty rationales for adopting generative AI, PEU emerged in this study as an initial entry point into the adoption process. This finding is consistent with the observations of Jarvie-Eggart et al. [9] that positive perceptions of usability can influence faculty adoption of engineering technologies. However, faculty in our study often encountered a different reality during implementation, as the perceived simplicity of AI tools did not translate into ease of pedagogical integration. Despite these challenges, perceived usefulness remained a sustained driver of continued exploration, confirming prior studies on the interdependence of PU and PEU in the technology adoption process [17,18]. Faculty balanced uncertainty about AI’s long-term educational implications with the desire to ensure students develop a baseline familiarity for future professional contexts without being compelled to rely on the technology in their day-to-day learning, reflecting a learner-centered orientation to technology adoption [19].

Our findings within the DOI and SCCT further extend existing research by illustrating how faculty adoption of AI is shaped by both contextual diffusion processes and purpose-driven motivations. Consistent with DOI, innovation characteristics such as trialability and observability played a central role in faculty adoption, as opportunities for personal experimentation and exposure through colleagues and professional settings reduced uncertainty and supported early engagement with AI. This aligns with prior work showing that the ability to try emerging technologies and observe their use within one’s professional community significantly influences adoption decisions in educational contexts [13,14].

Findings within TAM align with those of DOI, indicating the complementary nature of the two theories for understanding technology adoption. Complexity emerged not from technical difficulty, but from uncertainty surrounding pedagogical integration and the absence of established norms for effective AI use in learning environments. Similar tensions have been reported in studies of AI adoption in higher education, where ease of use coexists with ambiguity about appropriate instructional application [11]
From an SCCT perspective, faculty adoption of AI was closely tied to outcome expectations, performance goals, and anticipated attainment, particularly as they relate to student learning and career preparation. Reiterating Straub [20], adoption does not occur in a vacuum, yet many studies overlook this aspect. Faculty expected AI implementation and, in turn, utilization by

students to foster critical thinking, awareness, and improved learning strategies. Their persistence in adopting AI, largely influenced by the perceived usefulness of AI for students' learning, reflects SCCT's emphasis on outcome expectations as drivers of sustained engagement [15].

However, variability in performance goals across faculty, ranging from addressing immediate learning challenges to preparing students for an evolving workforce, highlights how adoption is guided by individualized pedagogical priorities rather than uniform objectives. Our finding indicates that faculty motivation to integrate emerging technologies is often linked to beliefs about students' future professional needs. Importantly, faculty uncertainty regarding AI's educational impact constrained clear performance benchmarks for some participants, suggesting that adoption may proceed even in the absence of well-defined outcome benchmarks. Together, these findings underscore that faculty adoption of AI is not solely a function of diffusion characteristics or acceptance factors, but a developmental process shaped by evolving beliefs through continued exploration. Viewed collectively, our integrated framework on TAM, DOI, and SCCT reveals how contextual exposure, experimentation, and purpose-driven intentions interact to support a learner-centered and forward-looking approach to AI adoption in engineering education.

Limitation

Our study is limited by the small sample size, consisting of three faculty members across two institutions. As a qualitative, exploratory investigation, the findings are not intended to be generalizable to the broader population of engineering educators. Instead, the study offers insights into how an integrated conceptual framework can capture faculty experiences with technology adoption.

Additionally, variations in institutional context, course type, and career stage may influence adoption processes in ways not fully represented within this sample. The limited number of participants restricts the ability to examine patterns across disciplines, faculty ranks, or institution types. Future research with a larger and more diverse sample of engineering faculty will be necessary to further test, refine, and extend the applicability of the integrated framework. Despite these limitations, the study contributes by demonstrating how TAM, DOI, and SCCT can be operationalized together to illuminate multiple dimensions of faculty adoption processes, offering a foundation for continued empirical expansion.

Implications

First, faculty development initiatives should move beyond technical training to support pedagogical sense-making around emerging technologies. Although AI tools were often perceived as easy to use, faculty experienced uncertainty in determining how to integrate them meaningfully into student learning. Professional development that emphasizes classroom implementation strategies and use cases may better support faculty navigating this complexity.

Second, faculty adoption was strongly influenced by trialability and observability, suggesting the importance of development initiatives that promote experimentation and peer learning. Opportunities for low-risk exploration, peer-led demonstrations, and informal communities of practice may be more effective than top-down mandates in supporting sustained and context-sensitive adoption.

Third, faculty adoption was guided by beliefs about student competencies, awareness, and career readiness, beyond efficiency or novelty. Faculty development efforts that foreground purpose - helping instructors align technology use with learning goals and professional preparation - may encourage learner-centered approaches that support student autonomy while ensuring baseline exposure to emerging technologies.

Future Work

In this work, we examined how an integrated conceptual framework, combining multiple theories, captured faculty experiences with the adoption of AI as an emerging technology. Our findings extend prior research on faculty technology adoption by centering faculty voices beyond predefined survey items or model-driven constructs. Building on this foundation, we plan to continue conducting interviews and extend the study to additional emerging technologies in order to better understand adoption processes as they relate to engineering student competency development. In future analyses, we also intend to conduct an inductive analysis of the data to identify aspects of the adoption process that the current conceptual framework did not fully capture.

References

1 - Yusuf, A., Pervin, N., & Román-González, M. (2024). Generative AI and the future of higher education: A threat to academic integrity or reformation? Evidence from multicultural perspectives. International Journal of Educational Technology in Higher Education, 21(1), 21. https://doi.org/10.1186/s41239-024-00453-6

2 - Bravo, F. A., & Cruz-Bohorquez, J. M. (2024). Engineering Education in the Age of AI: Analysis of the Impact of Chatbots on Learning in Engineering. Education Sciences, 14(5), 484. https://www.mdpi.com/2227-7102/14/5/484

3 - Bachiri, Y. A., & Mouncif, H. (2023). Artificial Intelligence System in Aid of Pedagogical Engineering for Knowledge Assessment on MOOC Platforms: Open EdX and Moodle. Int. J. Emerg. Technol. Learn., 18(5), 144-160.

4 - Kavianpour, A. (2024, June). Teaching Programming Languages by Two Teachers: Instructor and ChatGPT. In 2024 ASEE Annual Conference & Exposition.

5 - Wang, Y., Liu, C., & Tu, Y.-F. (2021). Factors Affecting the Adoption of AI-Based Applications in Higher Education: An Analysis of Teachers Perspectives Using Structural Equation Modeling. Educational Technology & Society, 24(3), 116–129. https://www.jstor.org/stable/27032860

6 - Abulail, R. N., Badran, O. N., Shkoukani, M. A., & Omeish, F. (2025). Exploring the Factors Influencing AI Adoption Intentions in Higher Education: An Integrated Model of DOI, TOE, and TAM. Computers, 14(6), 230. https://doi.org/10.3390/computers14060230

7 - Saihi, A., Ben-Daya, M., Hariga, M., & As' ad, R. (2024). A Structural equation modeling analysis of generative AI chatbots adoption among students and educators in higher education. Computers and Education: Artificial Intelligence, 7, 100274.

8 - Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. Computers & Education, 128, 13-35. https://doi.org/https://doi.org/10.1016/j.compedu.2018.09.009

9 - Jarvie-Eggart, M., Stockero, S. L., & Owusu-Ansah, A. (2024). Factors influencing faculty's adoption of engineering technology: A qualitative study. Computers and Education Open, 7, 100221.

10 - Simelane, P.M. and Kittur, J. (2025), Use of Generative Artificial Intelligence in Teaching and Learning: Engineering Instructors' Perspectives. Computer Applications in Engineering Education, 33: e22813. https://doi.org/10.1002/cae.22813

11 - Yadegari, M., Mohammadi, S., & Masoumi, A. H. (2024). Technology adoption: an analysis of the major models and theories. Technology Analysis & Strategic Management, 36(6), 1096-1110. https://doi.org/10.1080/09537325.2022.2071255

12 - Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. Management Science, 35(8), 982-1003. http://www.jstor.org/stable/2632151

13 - Rogers, E. M. (2003). Diffusion of innovations (5th ed.). Free Press.

14 - Al-Rahmi, W. M., Yahaya, N., Aldraiweesh, A. A., Alamri, M. M., Aljarboa, N. A., Alturki, U., & Aljeraiwi, A. A. (2019). Integrating Technology Acceptance Model With Innovation Diffusion Theory: An Empirical Investigation on Students' Intention to Use E-Learning Systems [Periodical]. IEEE Access, Access, IEEE, 7, 26797-26809. https://doi.org/10.1109/ACCESS.2019.2899368

15 - Lent, R. W., Brown, S. D., & Hackett, G. (1994). Toward a Unifying Social Cognitive Theory of Career and Academic Interest, Choice, and Performance. Journal of Vocational Behavior, 45(1), 79-122. https://doi.org/https://doi.org/10.1006/jvbe.1994.1027
16 - Lent, R. W., Sheu, H.-B., Miller, M. J., Cusick, M. E., Penn, L. T., & Truong, N. N. (2018). Predictors of science, technology, engineering, and mathematics choice options: A meta-analytic path analysis of the social–cognitive choice model by gender and race/ethnicity. Journal of counseling psychology, 65(1), 17.
17 - Álvarez-Marín, A., Velázquez-Iturbide, J. Á., & Castillo-Vergara, M. (2021). Technology Acceptance of an Interactive Augmented Reality App on Resistive Circuits for Engineering Students. Electronics, 10(11), 1286. https://doi.org/10.3390/electronics10111286
18 - K. Cook-Chennault and I. Villanueva, "An initial exploration of the perspectives and experiences of diverse learners' acceptance of online educational engineering games as learning tools in the classroom," 2019 IEEE Frontiers in Education Conference (FIE), Covington, KY, USA, 2019, pp. 1-9, doi: 10.1109/FIE43999.2019.9028605.
19 - Marbach-Ad, G., & Hunt Rietschel, C. (2016). A case study documenting the process by which biology instructors transition from teacher-centered to learner-centered teaching. CBE—Life Sciences Education, 15(4), ar62.
20 - Straub, E. T. (2009). Understanding Technology Adoption: Theory and Future Directions for Informal Learning. Review of Educational Research, 79(2), 625-649. https://doi.org/10.3102/0034654308325896