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VALIDATION OF PRE-SERVICE CHEMISTRY TEACHERS' ACCEPTANCE AND USE OF GENERATIVE ARTIFICIAL INTELLIGENCE SCALE: CONFIRMATORY FACTOR ANALYSIS

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Abstrak

Perkembangan pesat kecerdasan buatan generatif (GenAI) telah mengubah praktik pendidikan dengan memungkinkan munculnya bentuk baru dalam konstruksi pengetahuan, pemecahan masalah, dan dukungan pembelajaran. Integrasi yang semakin luas dalam konteks akademik menimbulkan pertanyaan penting mengenai bagaimana calon guru memandang dan mengadopsi teknologi ini. Penelitian ini bertujuan untuk mengkaji penerimaan dan penggunaan GenAI pada calon guru kimia dengan mengintegrasikan Unified *Theory of Acceptance and Use of Technology 2 (UTAUT2)* dan *Theory of Planned Behavior (TPB)* dalam kerangka pengukuran yang telah divalidasi. Penelitian ini menggunakan metode survei kuantitatif dengan desain potong lintang terhadap 240 mahasiswa calon guru Generasi Z melalui kuesioner terstruktur yang mencakup konstruk ekspektasi kinerja, ekspektasi usaha, norma subjektif, kondisi fasilitasi, kebiasaan, sikap, kontrol perilaku persepsian, niat perilaku, dan penggunaan AI. Analisis *Confirmatory Factor Analysis (CFA)* digunakan untuk menguji model orde pertama dan orde kedua. Hasil penelitian menunjukkan bahwa model memiliki kecocokan yang baik serta reliabilitas dan validitas yang kuat. Ekspektasi kinerja, ekspektasi usaha, dan norma subjektif berpengaruh signifikan terhadap sikap dan niat perilaku, sementara kondisi fasilitasi dan kontrol perilaku persepsian mendukung penggunaan AI. Niat perilaku menjadi prediktor terkuat terhadap penggunaan aktual. Secara keseluruhan, adopsi AI dipengaruhi oleh faktor psikologis, sosial, dan kontekstual, sehingga diperlukan pendekatan holistik dalam pendidikan calon guru.

Kata Kunci: *Generative Artificial Intelligence, Pre-service Chemistry Teachers, UTAUT2, TPB, Confirmatory Factor Analysis*

Abstract

The rapid development of generative artificial intelligence (GenAI) is transforming educational practices by enabling new forms of knowledge construction, problem-solving, and instructional support. Its growing integration into academic contexts has raised important questions about how future teachers perceive and adopt these technologies. This study aims to examine pre-service chemistry teachers' acceptance and use of GenAI by integrating the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and the Theory of Planned Behavior (TPB) within a validated framework. A quantitative cross-sectional survey was conducted with 240 Generation Z pre-service teachers using a structured questionnaire covering constructs such as performance expectancy, effort expectancy, social norms, facilitating conditions, habit, attitude, perceived behavioral control, behavioral intention, and AI use.

Confirmatory Factor Analysis (CFA) was applied to test both first-order and second-order models. The findings indicate that the proposed model achieved acceptable goodness-of-fit and strong reliability and validity across constructs. Performance expectancy, effort expectancy, and social norms significantly influenced attitudes and behavioral intention, while facilitating conditions and perceived behavioral control supported AI use. Behavioral intention emerged as the strongest predictor of use. Overall, the study highlights that AI adoption is shaped by interconnected psychological, social, and contextual factors, emphasizing the need for holistic teacher education strategies.

Keyword: Generative Artificial Intelligence, Pre-service Chemistry Teachers, UTAUT2, TPB, Confirmatory Factor Analysis

INTRODUCTION

The rapid emergence of generative artificial intelligence (GenAI) has introduced new modes of content creation, problem-solving, and communication that extend beyond the capabilities of traditional educational technologies. In recent years, GenAI tools such as ChatGPT, Gemini, Claude, and Copilot have become integrated into academic workflows, supporting writing, conceptual explanation, simulation, coding, and instructional design tasks (Lee, Huang, & Wu, 2025; Valeri, Nilsson, & Cederqvist, 2025). This shift has prompted debates on how AI will alter knowledge production, assessment, and instructional practices, while simultaneously creating new pedagogical opportunities for personalized feedback, inquiry-based learning, and computational support. Within chemistry education, generative AI is particularly relevant because these disciplines are inherently experimental, data-driven, and computationally oriented, making them well positioned to benefit from AI-supported modeling, visualization, and exploratory learning tasks (Leon, Lipuma, & Oviedo-Torres, 2025; Zeeshan, Hämäläinen, & Neittaanmäki, 2024).

Teacher education has become a critical domain for understanding how generative AI will be adopted in future classrooms. Pre-service teachers function as the next generation of instructional leaders who will determine whether and how emerging digital tools are integrated into curriculum and pedagogy. Their beliefs, attitudes, and technological dispositions shape instructional decision-making and influence long-term adoption behaviors (Bas & Kiraz, 2025). Chemistry pre-service teachers are especially important in this context, as chemistry curricula traditionally drive early adoption of digital technologies and are central to ongoing educational digital transformation efforts. If chemistry teachers perceive AI as pedagogically useful, accessible, and aligned with their disciplinary goals, they are more likely to incorporate it into future instructional settings (Pérez, et. al., 2025).

Generation Z constitutes the primary demographic population within contemporary teacher preparation programs. As digital natives, Gen Z learners have grown up with algorithmic platforms, mobile devices, and interactive technologies that shape their cognitive habits, communication styles, and expectations of learning environments (Merzifonluoglu & Gunes, 2025; Ningthias, & Qudratuddarsi, 2025). Although Gen Z learners exhibit familiarity and comfort with digital tools, familiarity does not automatically translate into pedagogical readiness. Many pre-service teachers can use AI for academic assistance, but remain uncertain about its instructional legitimacy, accuracy, ethical implications, and alignment with assessment practices. Studying Gen Z chemistry pre-service teachers, therefore, provides insight into how digital nativity intersects with AI adoption within professional preparation contexts (Karaca, 2025; Qudratuddarsi & Meivawati, 2025).

Chemistry pre-service teachers are uniquely important in generative AI adoption research because chemistry as a discipline possesses characteristics that strongly intersect with the capabilities of AI-driven technologies. Chemistry learning involves abstract visualization, symbolic representation, laboratory experimentation, computational reasoning, and data interpretation, all of which can be supported through generative AI tools capable of simulation, explanation, modeling, and interactive feedback. Compared to several other disciplines, chemistry education more frequently integrates digital laboratories, molecular visualization software, virtual simulations, and inquiry-based experimentation that require technological adaptation from teachers (Cetin, Eymur, & Erenler, 2024). These conditions position chemistry pre-service teachers at the intersection between scientific reasoning and educational technology integration. In addition, chemistry teachers often serve as facilitators of problem-solving and experimental inquiry, which requires them to evaluate the pedagogical legitimacy, accuracy, and ethical implications of AI-generated scientific content in classroom and laboratory contexts (Çolak Yazıcı, 2026).

The adoption of generative AI in education is not solely a technical issue; it is mediated by psychological, social, and contextual processes. Technology acceptance research has consistently demonstrated that individuals' willingness to adopt digital tools is shaped by perceptions of usefulness, ease of use, habit, motivation, social influence, and perceived control (Grassini, Aasen, & Møgelvang, 2024). The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) synthesizes these constructs and has been widely applied in consumer-oriented technology adoption research. In educational settings, UTAUT2 has been used to examine teachers' adoption of e-learning platforms, learning management systems, mobile applications, and other digital instructional tools. However, generative AI introduces qualitatively different interactions characterized by co-creative engagement, open-ended output generation, and cognitive offloading, suggesting that classical educational technology adoption scales may not fully reflect adoption mechanisms for AI-enabled tools (Arbulú Ballesteros, et. al., 2024; Perera, et. al., 2025).

The Theory of Planned Behavior (TPB) provides an additional layer of explanatory insight. TPB emphasizes attitudes, subjective norms, and perceived behavioral control (PBC) as predictors of behavioral intention. Applied to generative AI adoption, attitudes may reflect beliefs about AI's educational value, subjective norms may reflect peer and institutional influence, and PBC may reflect perceived capability and resource availability. Integrating UTAUT2 and TPB therefore provides a more comprehensive theoretical foundation for measuring AI acceptance and behavioral intention, capturing both performance-oriented and normative-control mechanisms relevant to professional decision-making (Greitemeyer, & Kastenmüller, 2024).

Despite the growing relevance of generative AI for education, empirical research on pre-service teachers remains limited. Current studies tend to focus on students' AI use in higher education, faculty perceptions of AI, academic integrity concerns, and ethical guidelines (Albadarin, Saqr, Pope, & Tukiainen, 2024; García-López, González, Ramírez-Montoya, & Molina-Espinosa, 2025; Montenegro-Rueda, Fernández-Cerero, Fernández-Batanero, & López-Meneses, 2023). Far fewer studies examine pre-service teachers' readiness to integrate AI into future classrooms. Within the smaller body of teacher-focused AI research, most investigations emphasize AI literacy, teacher beliefs, or the instructional potential of AI-enhanced tools, rather than psychological adoption processes. This gap is salient in chemistry teacher education, where AI may shape inquiry, experimentation, and model-based reasoning. Another important gap in the literature concerns measurement instruments (Ilić, Ivanović, & Klašnja-Milićević, 2024; Valeri, Nilsson, & Cederqvist, 2025). Few validated scales exist for capturing pre-service teachers' acceptance and use of generative AI. Existing technology acceptance measures were developed for earlier digital innovations such as e-learning, mobile learning, or learning management systems. These instruments may fail to capture motivational, habitual, or contextual constructs associated with generative AI. Without validated instruments, researchers lack the ability to reliably evaluate AI adoption mechanisms, while policymakers and teacher educators lack evidence-based tools for assessing readiness and designing targeted interventions (Köhler, & Hartig, 2024; Luo, & Zou, 2025; Nemt-Allah, Khalifa, Badawy, Elbably, & Ibrahim, 2024).

Scale validation studies are essential in this context because adoption constructs in UTAUT2 and TPB are latent psychological variables that must be operationalized through observable indicators. Confirmatory Factor Analysis (CFA) provides a methodological framework for testing factorial validity, dimensionality, internal consistency, and convergent-discriminant validity of such instruments. Applying CFA to generative AI adoption research enables scholars to model hierarchical relationships among constructs and evaluate whether AI acceptance can be conceptualized as a higher-order factor encompassing performance, motivation, habit, attitudes, norms, and perceived control (Görgülü, Coşkun, Demir, & Sipahioğlu, 2025; Küchemann, Rau, Schmidt, & Kuhn, 2024). Such modeling aligns with contemporary behavioral research trends that emphasize a multidimensional conceptualization of technology adoption rather than single-construct, model-driven approaches. Pre-service teachers operate within institutional and social ecosystems that influence how they evaluate and appropriate generative AI. Teacher preparation institutions are increasingly expected to integrate AI literacy, digital competencies, and instructional design skills into curricula. However, institutional strategies for preparing teachers for AI-mediated learning environments remain uneven. Some teacher education programs provide optional exposure to AI tools, while others are only beginning to explore curricular integration. If pre-service teachers graduate without adequate preparation, they may face future classrooms in which students already use AI as a cognitive assistant, creating misalignment between student practices and instructional expectations (Abdaljaleel, et. al., 2023).

Generative AI also raises deeper pedagogical questions that influence pre-service teachers' attitudes and adoption behaviors. If AI can generate explanations, scaffold problem-solving, and simulate inquiry, the teacher's role shifts toward mentoring, contextualizing, and evaluating student learning. Teachers must develop competencies in critical evaluation of AI-generated output, designing AI-influenced learning activities, and addressing ethical issues such as misinformation, plagiarism, equity, and authorship (Chun, Ning, Chen & Wijaya, 2025; Gümüş & Mehmet, 2025; Ning, Zhang, Yao, Fang, Xu & Wijaya, 2025). These emerging competencies position AI as more than a tool; it becomes a mediator of cognition that requires conceptual and pedagogical reframing. Therefore, the research question for this study: How does the integrated UTAUT2–TPB framework explain pre-service chemistry teachers' acceptance and use of Generative Artificial Intelligence (GenAI)?

METHOD

Research Design

This study used a quantitative, survey-based methodology gather and analyze numerical data from participants' standardized responses. Its objective was to examine pre-service chemistry teachers' acceptance and use of Generative Artificial Intelligence at a single point in time, without altering their environment or influence their responses (Fischer, Boone, & Neumann, 2023). Accordingly, a cross-sectional research design was selected to provide a one-time snapshot of the participants' competencies. This approach was beneficial because it avoided challenges often associated with longitudinal studies, such as participant attrition and shifts in external conditions that could affect findings. Employing a quantitative lens also increased the study's objectivity by treating data as measurable indicators and limiting the potential for researcher bias (Hodge, 2020; Qudratuddarsi, Meivawati, & Saputra, 2024).

Research Subject

The study involved 240 Generation Z pre-service chemistry teachers who were selected using convenience sampling. Although this sampling technique enabled quick and practical access to respondents, it can limit the extent to which findings apply to a broader population (Obilor, 2023). Even so, the sample remained highly relevant because the participants were familiar with technology in both academic and everyday contexts. Participant demographics are outlined in Table 1, indicating that 31.25% of the respondents were male and 68.75% were female, with females forming the majority. In terms of academic year, 29.17% were first-year students, 40.83% were second-year students, 30.00% were third-year students.

Table 1. Sample of the study

Sample	N	Percentage
Gender		
Male	75	31.25%
Female	165	68.75%
Year of study		
First year	70	29.17%
Second year	98	40.83%
Third Year	72	30.00%
Total	240	100 %

Instrument

The questionnaire utilized in this study was adapted from Habibi, Mukminin, Octavia, Wahyuni, Danibao, & Wibowo (2024) and revalidated to ensure its relevance to the current research setting. Content validity was verified by two specialists in educational technology, who evaluated whether the instrument effectively captured the intended constructs and aligned with the study's objectives. The Content Validity Index (CVI) based on their evaluations was 0.91, indicating a high level of agreement. The measure for assessing acceptance and use of Generative Artificial Intelligence was designed by combining two theoretical models: the Unified Theory of Acceptance and Use of Technology 2

(UTAUT2) and the Theory of Planned Behavior (TPB). The final instrument was composed of multiple sub-dimensions, including Subjective Norms (SN), Performance Expectancy (PE), Effort Expectancy (EE), Hedonic Motivation (HM), Facilitating Conditions (FC), Habit (H), Attitude (AT), Perceived Behavioral Control (PBC), Behavioral Intention (BI), and AI Use (AIU). Each sub-construct was represented by a set of indicators, with three items for PE, EE, HM, PBC, BI, and AIU; four items for FC, H, and AT; and five items for SN. Through deliberate adaptation, expert validation, and grounding in established theoretical frameworks, the instrument was ensured to be contextually appropriate and methodologically sound for examining pre-service teachers' acceptance and utilization of Artificial Intelligence.

Data Collection

Data collection was carried out using Google Forms, which aligns with sustainable and environmentally friendly research practices by reducing paper use, while also enhancing efficiency and minimizing potential errors from manual data entry The use of a digital platform provided the added benefit of real-time response tracking, enabling the researcher to monitor data quality promptly and address any inconsistencies (Hasan & Bakar, 2022). To further strengthen the reliability of the responses, the researcher maintained an active presence during data collection. This ensured that participants could seek clarification whenever survey items were unclear, thereby reducing misinterpretation and enhancing the instrument's construct validity. In addition, the researcher's supportive presence fostered a more comfortable and trustworthy atmosphere, which likely encouraged participants to answer truthfully and thoughtfully. Participation was strictly voluntary, and participants were explicitly informed that their responses would remain confidential and would not affect their academic standing or evaluations in any way. These ethical assurances are consistent with best practices in educational research, as they protect participant autonomy, minimize coercion, and uphold the integrity and credibility of the dataset. By combining digital efficiency, methodological rigor, and strong ethical safeguards, the study ensured both data quality and research trustworthiness (Jaiswal, 2024; Ulum, Basuki, & Eliasa, 2023).

Data Analysis

Confirmatory Factor Analysis (CFA) was applied to examine the measurement model and test the relationships between observed indicators and latent constructs. The first-order model assessing how individual items loaded onto their respective latent factors (Ramírez, et. al., 2025; Rogers, 2024). Model fit was assessed using standard goodness-of-fit indices such as χ^2, RMSEA, CFI, and TLI. Factor loadings were inspected to determine the strength of associations between items and latent dimensions. Composite Reliability (CR) values and Average Variance Extracted (AVE) were calculated to assess internal consistency and convergent validity, respectively, using recommended thresholds for measurement quality. Inter-construct correlations were also reviewed to determine the distinctiveness of the latent dimensions and to observe the conceptual relationships among factors within the proposed model (Serra, Alves, & Pinheiro, 2025).

RESULT AND DISCUSSION

Goodness of Fit

Confirmatory Factor Analysis (CFA) is a statistical technique used to test whether data fit a hypothesized measurement model, confirming the relationships between observed variables and underlying latent constructs. First-order CFA evaluates how well measured indicators (e.g., survey items) load onto their respective latent factors, ensuring each construct is valid and reliable. For example, dimensions like performance expectancy, effort expectancy, and attitudes may load onto a higher-order factor such as "AI acceptance and Use," providing stronger construct validity.

The structural equation modeling (SEM) results illustrate that the proposed model provides an acceptable fit to the data, as shown by the goodness-of-fit indices (χ^2 = 1423.409, RMSEA = 0.067, CFI = 0.917, TLI = 0.902). These values indicate that the model is statistically reliable for analyzing pre-service teachers' acceptance and use of artificial intelligence (AI). Each latent construct, including social norms (SN), performance expectancy (PE), effort expectancy (EE), facilitating conditions (FC), hedonic motivation (HM), attitude (AT), habit (H), perceived behavioral control (PBC), behavioral intention (BI), and actual AI use (AIU), was measured by multiple observed indicators, most of which had high factor loadings above 0.70, confirming their validity and reliability. The model further shows that performance expectancy and effort expectancy significantly influence both teachers' attitudes and behavioral intentions, highlighting the importance of perceived usefulness and ease of use. Social norms also play a substantial role in shaping attitudes and intentions, underscoring the value of peer and institutional influence. In addition, facilitating conditions and perceived behavioral control strongly support actual AI use, suggesting that adequate resources, training, and infrastructure are essential for successful implementation. Hedonic motivation and habit contribute positively to behavioral intention, indicating that enjoyment and routine in using AI tools encourage continued adoption. The strongest path in the model is from behavioral intention to actual AI use, with a coefficient of 1.00, demonstrating that intention is the most direct predictor of practice.

The second-order CFA results demonstrate that the measurement model achieves a satisfactory fit, indicated by χ^2 = 1502.040, RMSEA = 0.067, CFI = 0.912, and TLI = 0.902, all of which meet accepted thresholds for model adequacy. In this structure, multiple first-order latent constructs—such as social norms (SN), performance expectancy (PE), effort expectancy (EE), facilitating conditions (FC), hedonic motivation (HM), habit (H), attitude (AT), perceived behavioral control (PBC), behavioral intention (BI), and actual AI use (AIU)—are integrated under a higher-order construct labeled AttitudeUse. This higher-order factor reflects the idea that teachers' attitudes and behaviors toward AI are not isolated, but rather emerge as a unified construct shaped by interconnected psychological, social, and contextual elements. The strong standardized loadings from first-order constructs (e.g., habit, PBC, and attitude showing coefficients above 0.90) onto the second-order factor indicate that these dimensions are particularly influential in shaping the overall AttitudeUse construct. Meanwhile, constructs like social norms and effort expectancy, though slightly lower, still contribute meaningfully by capturing external pressures and ease-of-use perceptions. This hierarchical representation highlights that pre-service teachers' willingness and ability to adopt AI depend not only on their individual perceptions of usefulness and enjoyment but also on structural supports, habitual patterns, and social influences. In practical terms, the second-order CFA underscores that fostering AI adoption in teacher training requires a holistic approach—addressing skills, resources, institutional support, and cultural acceptance simultaneously—since these diverse factors converge into a single overarching orientation toward AI use.

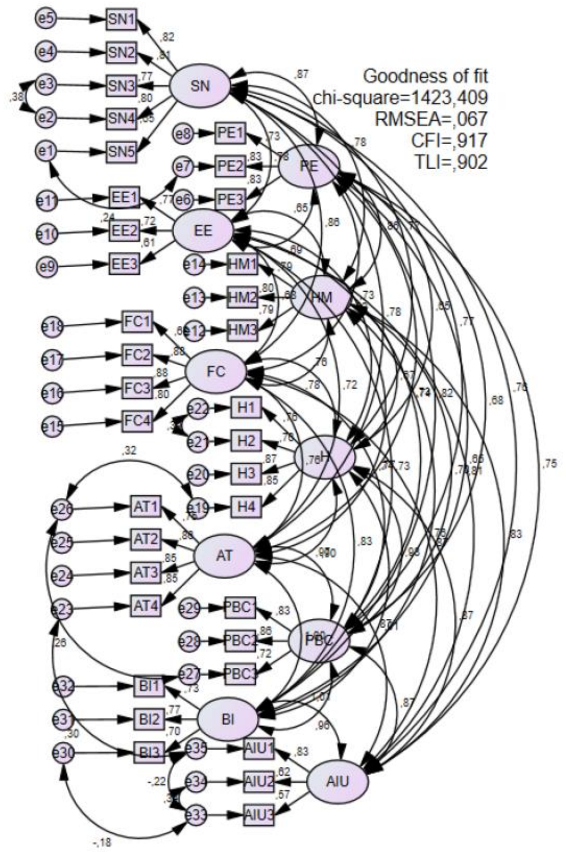

Figure 1. First-order Confirmatory Factor Analysis

Reliability

The results presented in Table 2 demonstrate that the instrument used to measure pre-service teachers' acceptance and use toward artificial intelligence possesses strong reliability and validity across all dimensions. Cronbach's alpha values ranged from 0.738 to 0.898, exceeding the commonly accepted threshold of 0.70, which indicates satisfactory to excellent internal consistency among the items. Similarly, the composite reliability (CR) values for all constructs were above 0.70, confirming that each dimension consistently represents the intended latent variable. The average variance extracted (AVE) values, ranging from 0.532 to 0.685, also met the recommended minimum of 0.50, thereby establishing adequate convergent validity. Dimensions such as Habit (α = 0.898; CR = 0.814; AVE = 0.672), Attitudes (α = 0.893; CR = 0.824; AVE = 0.685), and Facilitating Conditions (α = 0.877; CR = 0.804; AVE = 0.660) showed particularly high reliability, while constructs like Effort Expectancy (α = 0.743) and AI Use (α = 0.738) were acceptable though relatively lower. Importantly, the overall scale of AI attitude and use exhibited excellent reliability (α = 0.971; CR = 0.982) with sufficient convergent validity (AVE = 0.613), supporting the robustness of the measurement model.

Table 2. Reliability Result

No	Dimensions	Cronbach's alpha	CR	AVE
1	Subjective Norms (SN)	0.880	0.768	0.613
2	Performance Expectancy (PE)	0.836	0.793	0.645
3	Effort Expectancy (EE)	0.743	0.783	0.597
4	Hedonic Motivation (HM)	0.834	0.779	0.626
5	Facilitating Conditions (FC)	0.877	0.804	0.660
6	Habit (H)	0.898	0.814	0.672
7	Attitudes (AT)	0.893	0.824	0.685
8	Perceived Behavioral Control (PBC)	0.846	0.798	0.651
9	Behavioral Intention (BI)	0.776	0.714	0.532
10	AI Use (AIU)	0.738	0.756	0.562
11	AI attitude and use	0.971	0.982	0.613

Correlations among Dimensions

Table 3 presents the discriminant validity results for the measurement model, using inter-construct correlations among the ten dimensions of pre-service teachers' attitudes and use of artificial intelligence. The diagonal values are 1, representing the constructs themselves, while the off-diagonal values are the correlation coefficients between pairs of constructs. Overall, the correlations are positive and generally high, ranging from moderate (e.g., 0.650 between Effort Expectancy and Hedonic Motivation) to very strong (e.g., 0.972 between Attitudes and Perceived Behavioral Control and 0.980 between Behavioral Intention and AI Use). Such patterns suggest that the constructs are conceptually related but not redundant, thereby supporting the instrument's discriminant validity. Notably, strong correlations were observed among Habit, Attitudes, and Perceived Behavioral Control (all above 0.90), reflecting the close link between internalized behaviors, affective responses, and perceived behavioral control in shaping intention and actual AI use. Meanwhile, constructs like Effort Expectancy and Subjective Norms showed moderately strong relationships with other dimensions, highlighting their unique yet complementary roles in influencing attitudes and behaviors. Collectively, these findings indicate that while the dimensions are interrelated—as expected in behavioral intention and technology adoption frameworks—they remain empirically distinct, confirming the robustness of the measurement model.

Table 3. Correlation among dimensions

No	Dimensions	1	2	3	4	5	6	7	8	9	10
1	SN	1	.868	.781	.778	.858	.774	.783	.772	.815	.760
2	PE		1	.694	.859	.819	.651	.727	.682	.802	.752
3	EE			1	.650	.675	.727	.718	.743	.732	.654
4	HM				1	.782	.665	.762	.739	.817	.766
5	FC					1	.755	.762	.739	.817	.766
6	H						1	.905	.933	.915	.870
7	AT							1	.972	.976	.863
8	PB)								1	.969	.876
9	BI									1	.980
10	AIU										1

The findings indicate that pre-service chemistry teachers' adoption of generative AI is driven by a combination of cognitive, social, and contextual factors within an integrated behavioral framework. Key determinants such as performance expectancy and effort expectancy highlight that perceived usefulness and ease of use are central in shaping positive attitudes and intentions, while subjective norms emphasize the role of peer and institutional influence. Additionally, facilitating conditions and perceived behavioral control directly support actual AI use, suggesting that access to resources and confidence in using the technology are critical for implementation. The strong relationship between behavioral intention and actual use confirms that intention remains the most immediate predictor of practice. These results suggest that promoting AI adoption in teacher education requires not only technical training but also supportive environments, social encouragement, and opportunities for meaningful engagement, reinforcing the need for holistic and context-sensitive instructional strategies.

These findings have important implications for chemistry teaching and learning, particularly in preparing future chemistry teachers to integrate generative AI into inquiry-based and technology-enhanced instruction. Chemistry education involves abstract concepts, symbolic representations, molecular visualization, experimental design, and data interpretation, all of which can be supported through AI-assisted simulations, explanations, and adaptive feedback systems. The strong influence of performance expectancy and effort expectancy suggests that chemistry pre-service teachers are more likely to adopt AI when they perceive it as useful and easy to use in laboratory activities, problem-solving, and conceptual learning. Furthermore, the significant roles of facilitating conditions and perceived behavioral control indicate that institutional support, digital infrastructure, and AI literacy training are essential for successful classroom integration. The findings also highlight the importance of fostering positive attitudes, habitual engagement, and ethical awareness toward AI-mediated chemistry learning environments.

This study has several limitations that should be considered when interpreting the findings. First, the use of a cross-sectional design limits the ability to establish causal relationships among the variables, as data were collected at a single point in time. Second, the reliance on convenience sampling may reduce the generalizability of the results beyond the specific group of pre-service chemistry teachers involved in the study. Third, the data were based on self-reported measures, which may be subject to response bias such as social desirability or overestimation of AI use. Additionally, while the instrument demonstrated strong validity and reliability, it may not fully capture the evolving and context-dependent nature of generative AI adoption. Future research is recommended to employ longitudinal designs, more diverse samples, and mixed-methods approaches to provide deeper, more comprehensive insights into AI adoption in teacher education contexts.

The findings suggest several implications for teacher education and the integration of Generative Artificial Intelligence in instructional settings. The strong influence of performance expectancy and effort expectancy highlights the need for professional preparation programs to emphasize both the perceived usefulness of AI tools and the ease with which they can be incorporated into teaching practices. The role of social norms points to the importance of peer modeling and institutional encouragement in shaping willingness to experiment with new technologies, while the significance of facilitating conditions and perceived behavioral control indicates that effective AI adoption depends on access to resources, infrastructure, and training that enhance users' sense of capability. The contributions of hedonic motivation and habit suggest that AI-related coursework should enable enjoyable, routine, and low-risk engagement to normalize use. Together, these implications support multi-dimensional planning across instructional design, curriculum development, and institutional support systems in teacher education contexts.

CONCLUSION

This study investigated pre-service chemistry teachers' attitudes and use of Generative Artificial Intelligence by integrating UTAUT2 and TPB within a validated measurement framework. Using a cross-sectional survey administered to 240 Generation Z chemistry teacher candidates, the study demonstrated that attitudes and behavioral responses toward AI can be meaningfully explained through interconnected psychological, social, and contextual variables. The confirmatory factor analysis indicated that the proposed model achieved a satisfactory fit across both first-order and second-order structures, supporting the existence of a higher-order construct representing AI attitude and use. Performance expectancy, effort expectancy, social norms, hedonic motivation, habit, facilitating conditions, and perceived behavioral control were all found to contribute to behavioral intention and actual AI use, with intention emerging as the strongest direct predictor of use behavior. Reliability and validity indices further confirmed the instrument's robustness, suggesting that AI-related beliefs among future teachers are measurable, well-structured, and theoretically coherent. Collectively, these findings highlight that encouraging AI adoption in teacher education requires not only technological skill development but also supportive conditions, institutional culture, and positive behavioral orientations toward emerging digital tools.

Based on the findings, it is recommended that teacher education programs integrate generative AI into curricula through structured training, hands-on activities, and pedagogical guidance that emphasize both technical skills and critical evaluation of AI outputs. Institutions should also provide adequate infrastructure, access to AI tools, and supportive learning environments to strengthen pre-service teachers' confidence and habitual use. Additionally, fostering positive social norms through peer collaboration and instructor modeling can further encourage adoption. For future research, studies should explore longitudinal designs to examine changes in AI adoption over time, include more diverse and larger samples to enhance generalizability, and incorporate qualitative or mixed-method approaches to capture deeper insights into teachers' experiences, challenges, and ethical considerations related to AI integration in education.

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