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## Innovativeness and Optimism as Predictors of Generative AI Acceptance Among Pre-service Elementary School Teachers

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**ABSTRAK:** Penelitian ini mengkaji penerimaan Generative Artificial Intelligence pada mahasiswa calon guru sekolah dasar Generasi Z dengan memperluas model Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) melalui penambahan dua prediktor psikologis, yaitu keinovatifan dan optimisme. Seiring meningkatnya pemanfaatan Generative AI dalam dunia pendidikan, pemahaman mengenai bagaimana calon guru sekolah dasar memandang dan menerima teknologi ini menjadi penting untuk mendukung transformasi digital dan pengembangan kompetensi abad ke-21 dalam pendidikan. Penelitian ini menggunakan desain - survei kuantitatif dengan pendekatan *cross-sectional*. Data dikumpulkan dari 563 mahasiswa dari empat universitas di Indonesia melalui angket daring, dan dianalisis menggunakan *Partial Least Squares Structural Equation Modeling (PLS-SEM)* melalui SmartPLS. Hasil analisis model pengukuran menunjukkan bahwa seluruh konstruk memenuhi kriteria reliabilitas, validitas konvergen, dan validitas diskriminan, sementara indeks kelayakan model mengindikasikan bahwa model memiliki representasi yang memadai terhadap data empiris. Secara struktural, keinovatifan dan optimisme terbukti berpengaruh positif terhadap *performance expectancy*, *effort expectancy*, *facilitating conditions*, *habit*, dan *hedonic motivation*, dengan keinovatifan menjadi prediktor yang lebih kuat. Pada tingkat niat berperilaku, *performance expectancy*, *effort expectancy*, *facilitating conditions*, dan *habit* berpengaruh signifikan terhadap niat menggunakan Generative AI, sedangkan *hedonic motivation* tidak menunjukkan pengaruh signifikan. Model struktural berhasil menjelaskan 75,9% varians niat berperilaku, yang menunjukkan daya jelaskan yang kuat dalam konteks penerimaan Generative AI di pendidikan calon guru. Temuan penelitian ini menegaskan pentingnya faktor kognitif (misalnya persepsi manfaat dan kemudahan) serta faktor disposisi individu (misalnya keinovatifan dan optimisme) dalam membentuk penerimaan Generative AI. Secara teoretis, penelitian ini memperluas UTAUT2 dengan memasukkan konstruk kepribadian dalam studi penerimaan teknologi. Secara praktis, hasil penelitian mengimplikasikan perlunya program pendidikan guru menyediakan pengalaman otentik, dukungan institusional, serta ruang eksplorasi Generative AI untuk mendorong penggunaan yang bertanggung jawab dan efektif dalam pembelajaran sekolah dasar.

**Kata Kunci :** Generative AI acceptance; UTAUT2; keinovatifan; optimisme; Generasi Z

**ABSTRACT:** This study investigates Generative Artificial Intelligence acceptance among Generation Z pre-service elementary school teachers by extending the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model with innovativeness and optimism as additional psychological predictors. As Generative AI becomes increasingly embedded in educational practice, understanding how future elementary school teachers perceive and accept this technology is critical for informing teacher preparation and digital transformation initiatives. Using a quantitative, cross-sectional survey design, data were collected from 563 pre-service

teachers across four universities in Indonesia through an online questionnaire. Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS was used for data analysis. The measurement model demonstrated satisfactory reliability, convergent validity, and discriminant validity, while model fit indices indicated that the proposed model adequately represented the data. Results show that both innovativeness and optimism significantly predict performance expectancy, effort expectancy, facilitating conditions, habit, and hedonic motivation, with innovativeness emerging as the stronger personality-based determinant. Regarding behavioral intention to use Generative AI, performance expectancy, effort expectancy, facilitating conditions, and habit exhibit significant positive relationships, whereas hedonic motivation does not significantly influence intention. The structural model explains 75.9% of the variance in behavioral intention, indicating strong explanatory power within the context of Generative AI adoption in teacher education. The findings highlight the dual importance of cognitive evaluation (e.g., perceived usefulness and ease of use) and personal traits (e.g., innovativeness and optimism) in shaping Generative AI acceptance among pre-service elementary school teachers. Theoretically, the study extends UTAUT2 by demonstrating the value of incorporating personality-related constructs into contemporary AI acceptance studies. Practically, the results suggest that teacher education programs should provide structured opportunities for meaningful engagement with Generative AI tools while fostering mindsets that encourage experimentation and openness to technological change. These efforts may better prepare future teachers to integrate Generative AI responsibly and effectively in elementary education settings.

**Keywords:** Generative AI Acceptance; Generation Z; Innovativeness; Optimism; Structural Equation Modelling

## INTRODUCTION

Generative Artificial Intelligence (Generative AI) has emerged as a transformative force in contemporary education, reshaping how teaching, learning, and assessment are designed and implemented (Adeshola & Adepoju, 2024; Qudratuddarsi, & Meivawati, 2025). Unlike traditional educational technologies, Generative AI systems are capable of producing original content such as text, images, lesson plans, quizzes, and feedback, thereby supporting both instructional efficiency and pedagogical innovation. These capabilities allow educators to personalize learning experiences, adapt instructional materials to diverse learner needs, and provide immediate formative feedback, which can enhance student engagement and learning outcomes (Dewi, Qudratuddarsi, Ningthias, & Cinthami, 2024; Memarian, & Doleck, 2023; Rahman, & Watanobe, 2023).

In educational settings, Generative AI also supports administrative and instructional tasks, reducing teachers' workload and enabling them to focus more on higher-order teaching activities, such as mentoring and critical thinking facilitation (Elbanna & Armstrong, 2024; Qudratuddarsi, Fauziah, Agung & Yanti, 2025). Furthermore, Generative AI aligns well with learner-centered and constructivist approaches by promoting inquiry-based learning, creativity, and problem-solving. As education systems increasingly emphasize digital competence and 21st-century skills, the integration of Generative AI becomes essential for preparing learners to navigate technology-rich environments (Albadarin, Saqr, Pope, & Tukiainen, 2024; Saddia, Yanti, & Qudratuddarsi, 2025). However, the successful adoption of Generative AI in education depends not only on its technical capabilities but also on users' willingness to accept and use the technology effectively. Understanding the factors that influence Generative AI acceptance is therefore critical to ensuring its meaningful and responsible integration into

educational practice (Syamsi, Nugroho, Cahyani, & Retnaningsih, 2025; Wang, Pi, & Xie, 2025).

Generation Z pre-service teachers, particularly those majoring in elementary school teacher education, represent a unique group in the educational landscape. As digital natives, they have grown up surrounded by technology and are accustomed to rapid information access, digital communication, and interactive media (Akpınar, Kuloğlu, & Erdamar, 2022; Merzifonluoglu, & Gunes, 2025). Generative AI has strong potential to support this cohort by enhancing their learning experiences during teacher preparation and equipping them with tools that can be applied in future classroom practice. For pre-service elementary school teachers, Generative AI can assist in lesson planning, instructional material development, classroom assessment design, and reflective teaching practices. These tools are particularly valuable in elementary education, where teachers are required to teach multiple subjects and address diverse student needs. Generative AI can help pre-service teachers design age-appropriate content, differentiate instruction, and create engaging learning activities that foster creativity and critical thinking among young learners (Kalenda, Rath, Abugasea Heidt, & Wright, 2025; Lestari, Tari, Ramadhani, & Qudratuddarsi, 2025; Spasopoulos, Sotiropoulos, & Kalogiannakis, 2025).

Moreover, early exposure to Generative AI during teacher education programs can shape future teachers' professional beliefs, instructional strategies, and technology integration skills. As these pre-service teachers will eventually introduce technology to young learners, their perceptions and acceptance of Generative AI play a crucial role in determining how responsibly and effectively such technologies are used in elementary classrooms. (Chen, Rønningsbakk, & Huang, 2025). Therefore, examining Generative AI acceptance among this population is both timely and essential. Despite the growing availability of Generative AI tools in education, their successful implementation largely depends on users' acceptance and actual usage. Merely providing access to advanced technologies does not guarantee their effective adoption in educational contexts. As such, it is important to systematically examine the factors that influence individuals' intentions to use and actual use of Generative AI. Technology acceptance models provide a robust theoretical foundation for understanding these factors (Heine, & König, 2025); Syamsi, Nugroho, Cahyani, & Retnaningsih, 2025).

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) is particularly well suited for this purpose, as it extends earlier acceptance models by incorporating both cognitive and affective determinants of technology use. UTAUT2 explains technology adoption through key constructs such as performance expectancy, effort expectancy, facilitating conditions, hedonic motivation, habit, and behavioral intention. This framework has been widely applied in educational technology research due to its strong explanatory and predictive power (Grassini, Aasen, & Møgelvang, 2024). Using UTAUT2 to analyze Generative AI acceptance allows researchers to capture a comprehensive picture of how pre-service teachers perceive the usefulness, ease of use, and contextual support surrounding Generative AI. Given the novelty and complexity of Generative AI technologies, applying a well-established framework like UTAUT2 helps ensure theoretical rigor while providing practical insights into how acceptance and usage can be enhanced in teacher education contexts (Perera, et. al., 2025).

Beyond system-related and contextual factors, individual differences play a significant role in shaping technology acceptance, yet they remain underrepresented in

current UTAUT2 applications. Innovativeness and optimism are two dispositional traits that influence how individuals perceive and engage with new technologies (de Winter, Dodou, & Eisma, 2024). Innovativeness reflects a tendency to experiment with and adopt new ideas or technologies earlier than others, whereas optimism represents a positive belief that technology can enhance performance, efficiency, and overall quality of life. In the context of Generative AI, these traits are particularly salient, as Generative AI is disruptive, rapidly evolving, and often accompanied by uncertainty or ethical concerns in education. Individuals high in innovativeness are more inclined to explore Generative AI tools and tolerate ambiguity, while optimistic individuals prioritize the potential benefits of technology, thereby shaping perceptions of usefulness and enjoyment (Glaveanu & Maier, 2025).

For Generation Z pre-service teachers, innovativeness and optimism may function as critical psychological drivers of Generative AI acceptance. As future educators, their willingness to adopt and integrate Generative AI is influenced not only by institutional conditions but also by their personal dispositions toward technological change. Examining these traits enriches the theoretical lens, illuminating human factors that extend beyond conventional UTAUT2 constructs concerned primarily with performance, effort, and contextual enablers (Solomovich & Abraham, 2024; Wang & Zhang, 2023).

Although prior research has examined technology acceptance within education, empirical studies specifically focusing on Generative AI—particularly in teacher education—remain limited. Evidence on Generative AI acceptance among pre-service elementary teachers is especially scarce, despite their pivotal role in shaping future instructional practices. Moreover, while UTAUT2 has been widely validated, few studies have incorporated personality-related constructs such as innovativeness and optimism into the model when examining Generative AI acceptance. This represents a notable gap, as UTAUT2 lacks explanatory power regarding how personal dispositions interact with technological and contextual factors. Furthermore, research focusing on Generation Z pre-service teachers in developing countries remains underrepresented, even though cultural and educational contexts may influence adoption trajectories. To address these gaps, the present study integrates innovativeness and optimism into UTAUT2 to provide a more comprehensive understanding of Generative AI acceptance among Generation Z pre-service elementary school teachers.

## **METHODOLOGY**

### ***Research Design***

This study employed a quantitative survey research design to systematically collect and analyze numerical data obtained from participants' structured questionnaire responses. Using a survey approach, the research examined innovativeness and optimism as predictive factors of generative Artificial Intelligence (AI) acceptance among pre-service elementary school teachers at a single point in time, without introducing interventions or altering the participant group. A cross-sectional design was utilized to capture a snapshot of participants' levels of innovativeness, optimism, and generative AI acceptance, while avoiding common limitations associated with longitudinal studies, such as participant attrition and time-related external influences (Wang, & Cheng, 2020). The quantitative approach ensured objectivity and reliability, enabling statistical analyses to

identify relationships, patterns, and trends among the predictor variables and generative AI acceptance (Bloomfield, & Fisher, 2019).

**Research Subject**

A total of 563 Generation Z pre-service elementary school teachers took part in this study. Participants were selected through a convenience sampling method, which facilitated timely and accessible data collection, though it may somewhat limit the generalizability of the findings (Golzar, Noor, & Tajik, 2022). Despite this limitation, the sample was considered appropriate given the participants’ extensive engagement with technology in both everyday life and educational settings. The demographic profile of the respondents is presented in Table 1. The 563 respondents were drawn from four universities in Indonesia. In terms of gender distribution, 29.10% were male and 70.90% were female, indicating a predominance of female participants. With regard to academic standing, 27.05% of the participants were in their first year, 23.88% were in their second year, 31.53% were in their third year, and 17.54% were in their fourth year demonstrating a relatively balanced representation across different levels of study.

Table 1. Research subject

| Sample               | N   | Percentage |
|----------------------|-----|------------|
| <b>Gender</b>        |     |            |
| Male                 | 156 | 29.10%     |
| Female               | 380 | 70.90%     |
| <b>Year of Study</b> |     |            |
| First year           | 145 | 27.05%     |
| Second Year          | 128 | 23.88%     |
| Third year           | 169 | 31.53%     |
| Fourth year          | 94  | 17.54%     |
| Total                | 536 | 100%       |

**Instrument**

The primary data collection instrument used in this study was adapted from Habibi et al. (2023) to measure generative AI acceptance and from Wang and Zhang (2023) to assess innovativeness and optimism. The instrument was translated using a back-translation procedure to ensure linguistic accuracy and conceptual equivalence between the original and translated versions. This process involved translating the instrument into the target language and then independently translating it back into the original language to identify and resolve any inconsistencies or meaning shifts. To ensure the suitability of the instrument for the present context and participant population, a pilot study was conducted. The reliability of each construct was examined, with Cronbach’s alpha coefficients ranging from 0.85 to 0.96, indicating a very high level of internal consistency across all dimensions and confirming that the items reliably measured coherent constructs.

**Data Collection Procedure**

Data were collected using Google Forms, an online survey platform that facilitates environmentally friendly, paperless data collection while improving efficiency and minimizing errors associated with manual data entry. This digital approach also enabled researchers to access responses in real time. To ensure participants' clear understanding of the questionnaire items, the researcher was present during the survey administration to provide clarification when necessary. This assistance helped create a supportive atmosphere that encouraged sincere and well-considered responses. Participation was entirely voluntary, and respondents were assured that their responses would remain confidential and would have no impact on their academic evaluation. Adhering to these ethical principles was essential to maintaining the credibility and integrity of the data collected.

### ***Data Analysis***

Data analysis was conducted using SmartPLS software to implement partial least squares structural equation modeling (PLS-SEM), encompassing both measurement model and structural model evaluations (Hair et al., 2022; Vaithilingam et al., 2024). The selection of PLS-SEM was driven by its appropriateness for analyzing complex predictive relationships among the study's constructs, particularly as the main objective was to predict and explain Behavioral Intention (BI) among pre-service teachers. Moreover, PLS-SEM is well suited for studies with large sample sizes and offers efficient estimation and reliable results in models involving multiple latent variables and indicators (Memon, Ramayah, Cheah, Ting, Chuah, & Cham, 2021). Before assessing the measurement model, several data screening procedures were performed, including checks for missing data, verification of coding accuracy, and identification of outliers to ensure data quality. The measurement model was then evaluated by examining indicator loadings, internal consistency reliability (Cronbach's alpha and composite reliability), convergent validity using average variance extracted (AVE), and discriminant validity based on established After confirming the adequacy of the measurement model, the structural model was analyzed. Path coefficients, t-values, and p-values generated by SmartPLS were used to test the significance of the hypothesized relationships. In addition, effect sizes ( $f^2$ ) were assessed to determine the strength of each predictor's influence on the endogenous constructs, following the guidelines proposed by Hair et al. (2022) and Vaithilingam et al. (2024).

## **RESULT AND DISCUSSION**

### ***Descriptive Statistics and Normality***

Descriptive statistics are employed to summarize the central tendency and dispersion of the observed data. The mean values represent the average responses of participants to each measurement item, while the standard deviations indicate the extent of variability in respondents' perceptions. To assess data normality, skewness and kurtosis values were examined. In large-sample studies, skewness and kurtosis values within the acceptable range of  $\pm 2$  suggest that the data do not significantly deviate from a normal distribution (Mujeeb, Ali, & Anam, 2025; Pregoner, 2024; Ravid, 2024). Based on the results presented in the table, the mean scores across all measurement items range from 2.801 to 3.563, indicating that respondents generally expressed moderate to relatively positive perceptions of the constructs measured. The standard deviation values,

which range from 0.777 to 1.013, reflect low to moderate variability, suggesting a reasonable level of consistency in respondents' answers. Furthermore, the normality assessment shows that all skewness values fall between  $-0.285$  and  $0.157$ , while kurtosis values range from  $-0.367$  to  $0.670$ . All of these values are well within the recommended thresholds, indicating no substantial departure from normality. Therefore, the data can be considered approximately normally distributed and suitable for subsequent statistical analyses, such as regression analysis or structural equation modeling.

Table 2. Descriptive Statistics

| Item | M     | SD    | Kurt   | Skew   | Item | Mean  | SD    | Kurt   | Skew   |
|------|-------|-------|--------|--------|------|-------|-------|--------|--------|
| OP1  | 3.094 | 0.806 | 0.670  | -0.234 | EE1  | 2.837 | 0.940 | -0.075 | -0.017 |
| OP2  | 3.265 | 0.880 | 0.100  | -0.197 | EE2  | 3.094 | 0.884 | 0.201  | -0.185 |
| OP3  | 3.538 | 0.862 | -0.162 | -0.127 | HM2  | 3.407 | 0.811 | 0.155  | -0.047 |
| OP4  | 3.536 | 0.824 | -0.080 | 0.065  | HM3  | 3.446 | 0.799 | 0.105  | 0.157  |
| OP5  | 3.403 | 0.823 | 0.261  | -0.043 | FC1  | 3.394 | 0.837 | 0.237  | 0.118  |
| OP6  | 3.528 | 0.858 | 0.096  | -0.162 | FC2  | 3.382 | 0.850 | 0.407  | -0.001 |
| OP7  | 3.259 | 0.858 | 0.165  | -0.017 | FC3  | 3.089 | 0.863 | 0.149  | -0.006 |
| IN1  | 3.522 | 0.878 | -0.271 | 0.019  | FC4  | 2.995 | 0.956 | -0.039 | -0.099 |
| IN2  | 3.330 | 0.805 | 0.563  | 0.008  | H1   | 3.171 | 0.851 | 0.284  | -0.004 |
| IN3  | 3.469 | 0.864 | 0.304  | -0.285 | H2   | 3.037 | 0.920 | 0.063  | -0.005 |
| IN4  | 3.432 | 0.832 | 0.277  | -0.134 | H3   | 3.060 | 0.894 | 0.118  | -0.029 |
| IN5  | 3.249 | 0.861 | 0.276  | -0.150 | H4   | 3.215 | 0.825 | 0.341  | 0.040  |
| IN6  | 3.314 | 0.785 | 0.472  | -0.133 | BI1  | 3.304 | 0.792 | 0.315  | 0.005  |
| IN7  | 3.552 | 0.877 | -0.199 | 0.006  | BI2  | 3.098 | 0.867 | 0.282  | -0.092 |
| PE1  | 3.403 | 0.803 | 0.161  | 0.091  | BI3  | 3.133 | 0.903 | 0.135  | -0.077 |
| PE2  | 3.549 | 0.779 | -0.209 | 0.142  |      |       |       |        |        |
| PE3  | 3.382 | 0.801 | 0.466  | 0.056  |      |       |       |        |        |
| PE4  | 3.187 | 0.814 | 0.481  | -0.018 |      |       |       |        |        |

**Loading, Reliability and Convergent Validity**

Factor loadings, reliability, and convergent validity are key indicators for assessing measurement model quality. Factor loadings reflect how well each item represents its underlying construct. Reliability evaluates the internal consistency of items measuring the same construct, commonly assessed using Cronbach's alpha and composite reliability. Convergent validity indicates the degree to which items intended to measure a construct share a high proportion of variance, typically evaluated through factor loadings and average variance extracted (AVE). Based on the measurement model assessment, all constructs demonstrate satisfactory factor loadings, reliability, and convergent validity. The factor loading values for all items exceed the recommended threshold of 0.70, indicating that each indicator adequately represents its corresponding latent construct. In addition, Cronbach's alpha and rho-A values for all constructs are above 0.70, confirming strong internal consistency among the measurement items. The composite reliability (CR) values also surpass the acceptable level of 0.70, further supporting the reliability of the constructs. Moreover, the average variance extracted (AVE) values for all constructs are greater than 0.50, indicating that each construct explains more than half of the variance in its indicators. Overall, these results confirm

that the measurement model meets the required criteria for reliability and convergent validity.

Table 3 Loading, Realibility and Convergent Validity

| Factor | Item | Load  | Alpha | rho-A | CR    | AVE   |
|--------|------|-------|-------|-------|-------|-------|
| OP     | OP1  | 0.718 | 0.885 | 0.887 | 0.910 | 0.593 |
|        | OP2  | 0.751 |       |       |       |       |
|        | OP3  | 0.732 |       |       |       |       |
|        | OP4  | 0.810 |       |       |       |       |
|        | OP5  | 0.805 |       |       |       |       |
|        | OP6  | 0.743 |       |       |       |       |
|        | OP7  | 0.822 |       |       |       |       |
| IN     | IN1  | 0.784 | 0.912 | 0.913 | 0.930 | 0.656 |
|        | IN2  | 0.777 |       |       |       |       |
|        | IN3  | 0.855 |       |       |       |       |
|        | IN4  | 0.869 |       |       |       |       |
|        | IN5  | 0.812 |       |       |       |       |
|        | IN6  | 0.820 |       |       |       |       |
|        | IN7  | 0.746 |       |       |       |       |
| PE     | PE1  | 0.853 | 0.845 | 0.847 | 0.897 | 0.685 |
|        | PE2  | 0.845 |       |       |       |       |
|        | PE3  | 0.857 |       |       |       |       |
|        | PE4  | 0.751 |       |       |       |       |
| EE     | EE1  | 0.728 | 0.796 | 0.803 | 0.868 | 0.622 |
|        | EE2  | 0.793 |       |       |       |       |
|        | EE3  | 0.776 |       |       |       |       |
|        | EE4  | 0.852 |       |       |       |       |
| HM     | HM1  | 0.859 | 0.834 | 0.845 | 0.900 | 0.750 |
|        | HM2  | 0.852 |       |       |       |       |
|        | HM3  | 0.888 |       |       |       |       |
| FC     | FC1  | 0.879 | 0.857 | 0.872 | 0.903 | 0.700 |
|        | FC2  | 0.879 |       |       |       |       |
|        | FC3  | 0.850 |       |       |       |       |
|        | FC4  | 0.731 |       |       |       |       |
| H      | H1   | 0.901 | 0.913 | 0.917 | 0.939 | 0.793 |
|        | H2   | 0.875 |       |       |       |       |
|        | H3   | 0.897 |       |       |       |       |
|        | H4   | 0.888 |       |       |       |       |
| BI     | BI1  | 0.874 | 0.883 | 0.883 | 0.928 | 0.810 |
|        | BI2  | 0.907 |       |       |       |       |
|        | BI3  | 0.918 |       |       |       |       |

### ***Discriminant Validity***

Discriminant validity was assessed using the cross-loadings and Fornell–Larcker criterion within the PLS-SEM framework. Examination of cross-loadings showed that each indicator loaded more strongly on its intended latent construct than on any other constructs in the model. This indicates that the indicators adequately represent their respective constructs and do not overlap excessively with alternative constructs. Although some indicators exhibited moderate correlations with related constructs, none of the cross-loadings exceeded their primary loadings, confirming that each construct captures a distinct concept. In addition, discriminant validity was further evaluated using the Fornell–Larcker criterion. The results demonstrated that the square root of the average variance extracted (AVE) for each construct was greater than its correlations with other constructs. This finding indicates that each construct shares more variance with its own indicators than with other constructs in the model. Collectively, these results provide strong evidence that discriminant validity is well established for the measurement model

### ***Structural Model***

Variance Inflation Factor (VIF) is an indicator used to detect multicollinearity among predictor variables in structural equation modeling, where values below 5 generally suggest that collinearity is not problematic, and values below 3 are preferred for more conservative assessments (Hair et al., 2021). Meanwhile, model fit indices such as the Standardized Root Mean Square Residual (SRMR),  $d\_ULS$ ,  $d\_G$ , and chi-square are used to evaluate how well the proposed model reproduces the observed covariance matrix. An SRMR value below 0.08 indicates a good fit, while lower  $d\_ULS$  and  $d\_G$  values imply minimal discrepancies between empirical and model-implied correlations. Although chi-square is commonly reported, it is highly sensitive to sample size; therefore, researchers typically emphasize relative and residual-based fit indices. The VIF results indicate that all predictor constructs fall within acceptable collinearity thresholds. All VIF values were below the commonly accepted cut-off of 5 and mostly below the more conservative threshold of 3, suggesting that multicollinearity is not a serious concern in the structural model. This implies that the predictors contribute uniquely to the model and do not exhibit problematic overlap that would bias parameter estimation or interpretation. In terms of model fit, the SRMR value obtained (0.069) fell below the recommended maximum of 0.08, indicating a satisfactory degree of correspondence between the model-implied correlations and the empirical data. The  $d\_ULS$  and  $d\_G$  indices were relatively low, supporting the notion that residual discrepancies between observed and predicted matrices were minimal. Although the chi-square value was reported, its magnitude should be interpreted cautiously given its sensitivity to large sample sizes. Overall, these results confirm that the model demonstrates an acceptable fit and is theoretically and statistically appropriate for subsequent structural path analysis.

Table 4. VIF and Model Fit

| Factor | VIF         | Model      | Saturated Model |
|--------|-------------|------------|-----------------|
| OP     | 1.846-2.438 | SRMR       | 0.069           |
| IN     | 1.788-3.314 | d_ ULS     | 2.105           |
| PE     | 1.506-2.150 | d_ G       | 0.829           |
| EE     | 1.651-2.159 | Chi-square | 3701.252        |
| FC     | 1.875-3.507 |            |                 |
| HM     | 1.894-1.972 |            |                 |
| H      | 2.672-3.044 |            |                 |
| BI     | 2.054-3.055 |            |                 |

The structural model results illustrate the relationships among the study’s constructs and the strength of their respective indicators. All measurement items demonstrated strong loadings on their intended constructs, with values exceeding the recommended minimum threshold of 0.70, indicating satisfactory indicator reliability and confirming that the observed variables appropriately represent the latent constructs. The corresponding t-statistics further support this, showing that all item loadings were statistically significant. The model also reports the R<sup>2</sup> values for the endogenous constructs, reflecting the explanatory power of the predictors. Behavioral Intention (BI) demonstrated the highest explained variance (R<sup>2</sup> = 0.759), indicating that a substantial portion of pre-service teachers’ intention to use generative AI can be explained by the predictors included in the model. Performance Expectancy (PE), Effort Expectancy (EE), Hedonic Motivation (HM), Facilitating Conditions (FC), and Habit (H) also exhibited moderate levels of explained variance, with R<sup>2</sup> values ranging between 0.513 and 0.663. These findings suggest that both individual traits (i.e., innovativeness and optimism) and core UTAUT2 constructs collectively contribute to pre-service teachers’ perceptions and behavioral intentions toward generative AI.

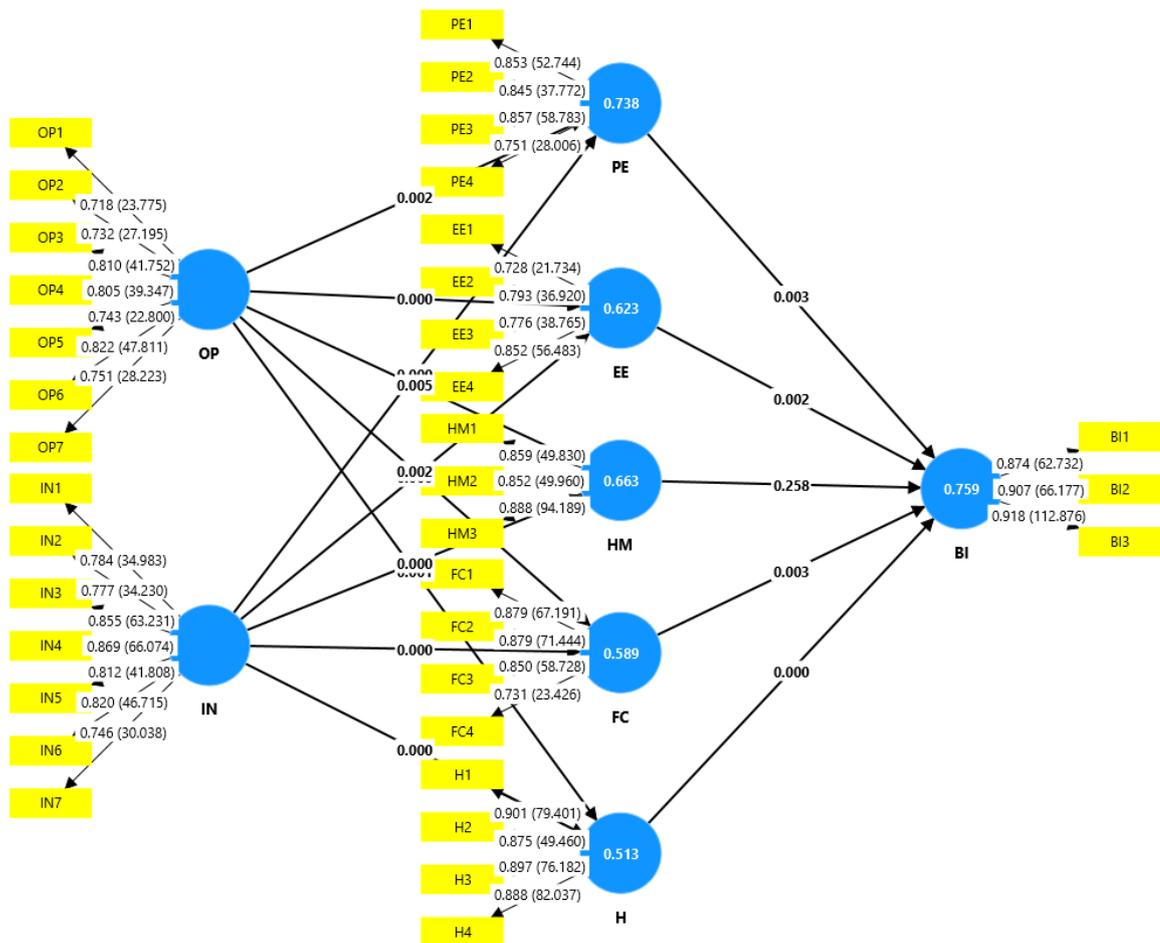


Figure 1. Structural Model

The structural model results provide evidence regarding the relationships among the latent constructs. Optimism (OP) demonstrated significant positive effects on Effort Expectancy (EE) ( $\beta = 0.253$ ,  $p < 0.001$ ), Facilitating Conditions (FC) ( $\beta = 0.224$ ,  $p = 0.002$ ), Habit (H) ( $\beta = 0.240$ ,  $p = 0.001$ ), Hedonic Motivation (HM) ( $\beta = 0.185$ ,  $p = 0.005$ ), and Performance Expectancy (PE) ( $\beta = 0.175$ ,  $p = 0.002$ ). These findings indicate that individuals with higher levels of optimism tend to perceive generative AI as easier to use, more enjoyable, more useful, and better supported by contextual resources, while also demonstrating a stronger tendency to form usage habits.

Innovativeness (IN) exhibited even stronger predictive power across the same UTAUT2 constructs. IN significantly influenced EE ( $\beta = 0.564$ ,  $p < 0.001$ ), FC ( $\beta = 0.569$ ,  $p < 0.001$ ), H ( $\beta = 0.502$ ,  $p < 0.001$ ), HM ( $\beta = 0.652$ ,  $p < 0.001$ ), and PE ( $\beta = 0.706$ ,  $p < 0.001$ ). These coefficients suggest that individuals who are more innovative are more inclined to explore and appreciate the potential of generative AI, perceiving it as useful, enjoyable, and supported by facilitating conditions. The substantially higher  $\beta$  values and t-statistics for IN compared to OP indicate that innovativeness serves as a stronger psychological predictor in this model.

Regarding Behavioral Intention (BI), PE ( $\beta = 0.151$ ,  $p = 0.003$ ), EE ( $\beta = 0.138$ ,  $p = 0.002$ ), FC ( $\beta = 0.188$ ,  $p = 0.003$ ), and H ( $\beta = 0.433$ ,  $p < 0.001$ ) significantly predicted intention to use generative AI. Among these, Habit exhibited the strongest influence,

suggesting that repeated or familiar technology use behavior is a key driver of BI. In contrast, Hedonic Motivation (HM) did not significantly predict BI ( $\beta = 0.054$ ,  $p = 0.258$ ), indicating that enjoyment alone may not be sufficient to drive usage intention in educational contexts focused on utility and performance.

Table 5. Structural Path Results and Hypothesis Testing

| H   | Relationship | $\beta$ | Mean  | SD    | T      | p     |
|-----|--------------|---------|-------|-------|--------|-------|
| H1  | OP -> EE     | 0.253   | 0.261 | 0.069 | 3.672  | 0.000 |
| H2  | OP -> FC     | 0.224   | 0.229 | 0.071 | 3.156  | 0.002 |
| H3  | OP -> H      | 0.240   | 0.245 | 0.070 | 3.423  | 0.001 |
| H4  | OP -> HM     | 0.185   | 0.191 | 0.066 | 2.781  | 0.005 |
| H5  | OP -> PE     | 0.175   | 0.181 | 0.058 | 3.040  | 0.002 |
| H6  | IN -> EE     | 0.564   | 0.556 | 0.070 | 8.093  | 0.000 |
| H7  | IN -> FC     | 0.569   | 0.565 | 0.070 | 8.141  | 0.000 |
| H8  | IN -> H      | 0.502   | 0.496 | 0.074 | 6.816  | 0.000 |
| H9  | IN -> HM     | 0.652   | 0.646 | 0.068 | 9.637  | 0.000 |
| H10 | IN -> PE     | 0.706   | 0.700 | 0.056 | 12.506 | 0.000 |
| H11 | PE -> BI     | 0.151   | 0.149 | 0.051 | 2.954  | 0.003 |
| H12 | EE -> BI     | 0.138   | 0.139 | 0.045 | 3.098  | 0.002 |
| H13 | FC -> BI     | 0.188   | 0.191 | 0.064 | 2.931  | 0.003 |
| H14 | H -> BI      | 0.433   | 0.431 | 0.055 | 7.850  | 0.000 |
| H15 | HM -> BI     | 0.054   | 0.054 | 0.048 | 1.132  | 0.258 |

The findings demonstrate that innovativeness and optimism significantly influence key UTAUT2 constructs associated with Generative AI acceptance, highlighting an important research gap in extending technology acceptance models beyond traditional expectancy and contextual variables. While UTAUT2 incorporates hedonic motivation, habit, and facilitating conditions, it does not explicitly account for individual-level cognitive traits that shape perceptions of emerging technologies. By integrating innovativeness and optimism into the model, this study shows that these dispositional factors exert meaningful effects on performance expectancy, effort expectancy, and habit, with innovativeness emerging as the stronger predictor. This suggests that individuals who are more open to novel technologies and more positive about their outcomes may internalize AI as both usable and valuable more rapidly. Moreover, behavioral intention to use Generative AI is driven largely by performance expectancy, effort expectancy, facilitating conditions, and habit, while hedonic motivation remains insignificant, indicating that utility outweighs enjoyment in Generation Z pre-service teachers.

Beyond these empirical findings, several implications can be identified. First, the study suggests that the acceptance of Generative AI in teacher education is not merely a technological issue, but also a psychological and dispositional one. Preparing future teachers to engage with AI requires fostering curiosity, openness to experimentation, and a positive orientation toward technological change. Teacher education programs may

therefore consider instructional approaches that encourage creative inquiry, reflective practice, and safe experimentation with AI tools. Second, the significant role of habit and perceived usefulness indicates that repeated and meaningful exposure to Generative AI throughout teacher preparation is preferable to sporadic or optional engagement, as sustained practice can cultivate familiarity and competence that support longer-term integration in professional contexts.

Embedding Generative AI in assignments, microteaching activities, lesson design, and assessment tasks may encourage continuous usage and enable future teachers to envision AI-supported instructional practices. Third, as pre-service elementary teachers will soon introduce AI-mediated tools to young learners, institutions must also attend to issues of critical digital literacy, pedagogical alignment, and ethical use of Generative AI. This includes guiding students to evaluate AI-generated content, recognize its limitations, and apply it responsibly. Collectively, these implications suggest the need for strategic curricular planning, coherent institutional support, and deliberate mindset development, offering direction for teacher education programs and policy actors in shaping environments conducive to responsible AI adoption within an increasingly AI-enhanced educational landscape.

## CONCLUSION

This study examined Generation Z pre-service elementary school teachers' acceptance of Generative AI by extending the UTAUT2 framework with two personality-related predictors: innovativeness and optimism. Using PLS-SEM with data from 563 students across four universities in Indonesia, the findings demonstrate that the proposed model has satisfactory reliability, validity, and overall fit, and explains a substantial proportion of variance in Behavioral Intention ( $R^2 = 0.759$ ). Optimism was found to significantly enhance effort expectancy, facilitating conditions, habit, hedonic motivation, and performance expectancy. However, innovativeness emerged as the stronger predictor across all UTAUT2 constructs, indicating that students who are more willing to explore and experiment with new technologies perceive Generative AI as more useful, easier to use, better supported, more enjoyable, and more easily integrated into their routines. These individual traits thus function as important psychological enablers of Generative AI integration in teacher education.

Regarding behavioral intention to use Generative AI, performance expectancy, effort expectancy, facilitating conditions, and habit all exerted significant positive effects. Habit was the strongest predictor, highlighting the central role of repeated use and routine formation in sustaining intention. In contrast, hedonic motivation did not significantly influence intention, suggesting that for pre-service elementary school teachers, pragmatic and utility-oriented considerations outweigh enjoyment when deciding whether to adopt Generative AI for academic and professional purposes. Theoretically, this study extends UTAUT2 by demonstrating the added explanatory value of innovativeness and optimism in the context of Generative AI and teacher education. Practically, the findings underscore

the need for teacher education programs to not only provide technical training on Generative AI tools but also cultivate innovative and optimistic mindsets through authentic tasks, reflective activities, and supportive learning environments. Future research could employ longitudinal designs, include behavioral use data, explore ethical and critical dimensions of Generative AI, and compare results across cultural contexts and teacher specializations to further enrich understanding of Generative AI adoption in education.

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