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# The Use of AI for Learning Planning Viewed from the UTAUT Perspective

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**Keywords**

generative artificial intelligence, lesson planning, UTAUT2, behavioral intention, vocational education, PLS-SEM, technology adoption

**Abstract**

This research examines the determinants influencing vocational high school teachers' behavioral intention and actual use of generative artificial intelligence (AI) in lesson planning, employing a modified Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework. A quantitative research design was implemented, utilizing purposive sampling to select 92 teachers from SMK Negeri 2 Salatiga who had prior experience with generative AI in instructional design. Data were collected through a structured Likert-scale questionnaire and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4, assessing construct validity, reliability, and structural relationships. The findings indicate that Behavioral Intention constitutes the most substantial predictor of Use Behavior ($\beta = 0.958$), significantly shaped by Hedonic Motivation, Habit, Price Value, Performance Expectancy, and Effort Expectancy. Notably, Lesson Planning exhibits a negative association with Use Behavior ($\beta = -0.378$), suggesting that rigid or bureaucratic planning frameworks may impede the integration of AI technologies. Demographic moderators, including age, gender, professional experience, educational attainment, and willingness, demonstrated no statistically significant effects. The study underscores that the adoption of AI in educational contexts is predominantly driven by motivational and perceptual constructs rather than demographic variables. The implications emphasize the necessity for adaptive lesson design, targeted teacher professional development focusing on technological pedagogical content knowledge (TPACK), and supportive policy frameworks to foster effective and contextually relevant AI integration in vocational education.

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## INTRODUCTION

Artificial Intelligence (AI) has attracted significant attention. AI has undergone several phases of development, but in recent years, AI has returned with the introduction of ChatGPT or Chat Generative Pre-trained Transformer, which was released on November 30, 2022 (Fui-Hoon Nah et al., 2023). ChatGPT is a natural language processing (NLP) system developed by OpenAI (OpenAI, 2023). ChatGPT is designed to create human-like conversations by understanding context and generating appropriate responses. ChatGPT is equipped with advanced features that make it a highly effective natural language processing technology. The system can recognize and respond contextually within a dialogue with relevance. Additionally, ChatGPT has the capability to provide answers in multiple languages (Deng & Lin, 2023).

The development of artificial intelligence has consequences and challenges that cause major changes in the world of education, making it a fundamental pillar in preparing future generations. Currently, AI technology can be used to facilitate the teaching and learning processes of both students and teachers, as well as to absorb and share knowledge more effectively (Taufik & Rindaningsih, 2024). AI has great potential for use in education, particularly in the learning planning stage. As one form of artificial intelligence, ChatGPT can help teachers design learning plans by considering various factors, such as determining learning objectives, selecting appropriate methods, models, strategies, techniques, and technologies that suit learning needs (Saputra & Serdianus, 2023). The emergence of AI has transformed learning models, created new demands, and changed the nature of education at various levels. Although technology is developing very rapidly, the role of teachers as the foundation in shaping students' personality, intellectuality, and insights remains irreplaceable. Teachers also have an important task to develop students' personalities so they can think openly and holistically (Taufik & Rindaningsih, 2024).

In the context of AI technology adoption in learning planning, the Unified Theory of Acceptance and Use of Technology (UTAUT) model explains that there are four main factors that influence a person's intention and behavior regarding technology use: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions (Viswanath Venkatesh, Michael G. Morris, 2003). Performance expectancy refers to the extent to which teachers believe AI can help improve the quality of their teaching. Effort expectancy refers to how easy it is to learn and use the technology. Social influence includes support from peers, school leaders, and the school environment as a whole. Facilitating conditions include facilities, training, and technical assistance that facilitate teachers' use of new technology (Watted, 2025).

In the world of education, implementing artificial intelligence for learning planning has now become a fundamental goal to improve the effectiveness of the teaching and learning process. Based on this perspective (Viswanath Venkatesh, Michael G. Morris, 2003), the UTAUT framework explains that technology acceptance depends on four factors: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. These factors are often used in research examining responses to technology in different learning environments. Recent research shows that teachers' acceptance of AI in developing learning plans is greatly influenced by how easy they feel this technology is to use and how much benefit they perceive from it (Cabero-Almenara et al., 2024; Watted, 2025). Therefore, there is a need to further explore how factors in the UTAUT framework contribute to teachers' intentions and actions regarding AI implementation in the learning planning process.

The development of AI offers great opportunities in education, especially in designing learning plans that are more structured, flexible, and effective. From a pedagogical perspective, teachers not only act as instructors but also as designers of learning experiences that are relevant and meaningful for students. This role becomes increasingly important in the context of the 21st century, where teachers are expected to be able to design learning environments that encourage student engagement, creativity, and digital competencies (Argyriou, 2025; Galeboe et al., 2025). In this regard, AI can be used to help teachers analyze student needs, design personalized materials for each individual, and directly monitor learning progress (Watted, 2025). Psychological and structural factors have a significant impact on AI adoption among teachers, as explained in the UTAUT model. According to this theory, AI technology adoption by teachers depends on several main factors: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. These factors determine the level of teachers' willingness to integrate AI into their learning processes (Venkatesh et al., 2016). Therefore, it is important to understand how teachers adopt AI technology to design effective strategies to support maximum implementation in the learning process (Cabero-Almenara et al., 2024).

In recent years, attention to the use of AI in education has continued to increase, especially regarding how teachers accept and adopt this technology (Liu-yun & Yuan, 2025; Putra et al., 2025). One theoretical approach widely used to understand this technology adoption process is the UTAUT. Watted (2025) found that teachers' perceptions of AI integration are greatly influenced by the four main dimensions of UTAUT: performance expectancy, effort expectancy, social influence, and facilitating conditions. Research by Benjamin & Dangwal (2025) confirms that social influence and ease of technology use are dominant factors in teachers' readiness to adopt AI in classrooms. In China, Zhao et al. (2025) stated that the main barriers to AI adoption stem from low performance expectancy and structural challenges such as teacher workload. Meanwhile, Moon (2025) developed a UTAUT-based technology acceptance model by adding cost-benefit perception, which plays a significant role in shaping teachers' intentions toward AI use. Alkhateeb et al. (2025), in the context of English language learning at universities in Saudi Arabia, confirmed that the availability of technological facilities and social support are determining factors for successful AI adoption by teachers. Ateş & Gündüzalp (2025) proposed a UTAUT2-based conceptual model in the context of STEM teachers, incorporating additional variables such as habit and intrinsic motivation. Adigun et al. (2025) highlighted the importance of technical training and readiness perception in influencing the intentions of inclusive teachers in Nigeria to use AI. Wu et al. (2025) added that risk perception, especially related to privacy and AI technology reliability, remains a major barrier to its use in physical education.

Although AI technology adoption in education shows significant development, particularly in supporting learning processes, studies that specifically examine how Vocational High School (SMK) teachers design learning by utilizing generative AI are still very limited. Research linking the UTAUT2 model with the context of vocational learning in Indonesia is also not widely found. Most studies applying UTAUT2 in explaining AI adoption behavior by educators are still centered in developed countries and Middle Eastern regions, such as China (Zhao et al., 2025), Saudi Arabia (Al-Amri & Al-Abdullatif, 2024), and Jordan (Alqaisi et al., 2025). These studies generally focus on higher education sectors or general teachers, so they are not entirely relevant for generalization to the Indonesian socio-cultural context, which has its own characteristics in the vocational education system. Additionally, longitudinal approaches that monitor changes in teachers' perceptions of AI use after training or practical interventions are also rarely encountered. Most previous studies use cross-sectional approaches that tend to be limited in describing long-term user perception dynamics (Khlaif et al., 2024).

Furthermore, the UTAUT2 model used in various studies is generally still applied standardly without adjustment to local contexts or addition of external constructs such as technology anxiety, usage habits, and trust in digital systems. Model development efforts have been conducted by Rana et al. (2024) who integrated trust and privacy aspects into UTAUT2 in the academic context of Bangladesh, and by Ateş & Gündüzalp (2025) in Turkey through a conceptual approach for STEM teachers. However, these studies have not specifically covered vocational dimensions. Additionally, quantitative approaches in studies of AI adoption by teachers still lack attention to pedagogical aspects and social meanings inherent in technology integration processes. Teachers do not only serve as technology users but also as learning designers who are contextually relevant and pedagogically and culturally meaningful (Panda, 2024).

This research attempts to address the current gap by examining how teachers view the use of AI technology in education and determining what factors influence their intention to use AI in teaching and learning activities, based on the UTAUT model. This research aims to gain relevant understanding about the social and cultural context of AI implementation in schools, which can then be useful for policy formulation, teacher training, and implementation of better teaching methods (Watted, 2025). Additionally, this research also seeks to explore in depth how teachers' perceptions are influenced by factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions, which are the four main components in the UTAUT model. By understanding these four factors, researchers can identify barriers and drivers related to AI technology implementation in educational environments, especially in schools with diverse social and cultural backgrounds. The findings of this research are very important in efforts to create more comprehensive and contextual technology implementation plans, and ensure that educational policies and teacher training can be adapted to real needs in the field, so that AI integration in learning methods is not only technologically meaningful but also socially and culturally meaningful (Viswanath Venkatesh, Michael G. Morris, 2003; Watted, 2025).

## METHODS

To analyze the adoption of Generative AI among teachers at SMK Negeri 2 Salatiga, researchers used purposive sampling with the following criteria: teachers who have used or frequently use Generative AI in the learning planning design process at SMK Negeri 2 Salatiga as subjects of this research. The research method used in this study employs a quantitative approach (Asrulla et al., 2023). The research stages are presented in Figure 1.

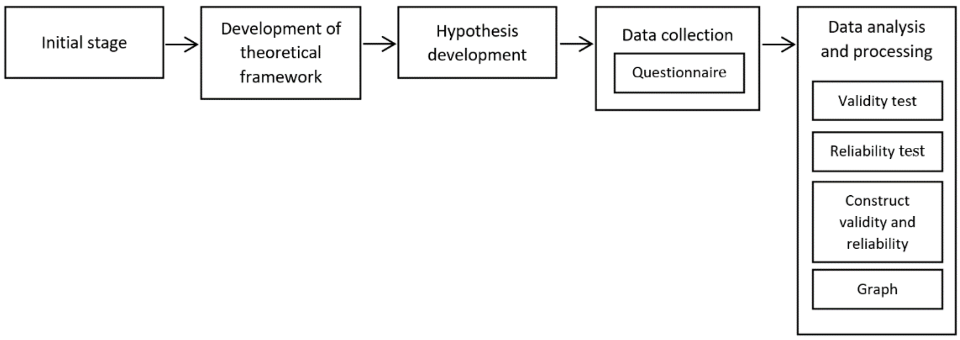


Figure 1. Research Stages

### Initial Research Stage

The initial stage of this research began with the researcher's discovery identifying problems regarding the low use of Generative AI in learning planning by teachers at SMK Negeri 2 Salatiga. Subsequently, the researcher conducted a deeper literature review study on the use of modified UTAUT2 theory with the addition of moderating variables, namely education level and willingness, as well as voluntariness of use variable, namely learning planning (Idrees & Ullah, 2024; Li et al., 2022; Narayan & Naidu, 2024).

### Development of Conceptual Framework

The conceptual framework created in this study is based on the modified UTAUT2 model with the addition of moderating variables, namely education level and willingness, as well as voluntariness of use variable, namely learning planning (Chen et al., 2021; Idrees & Ullah, 2024; Li et al., 2022; Narayan & Naidu, 2024). The research model used is presented in Figure 2 below:

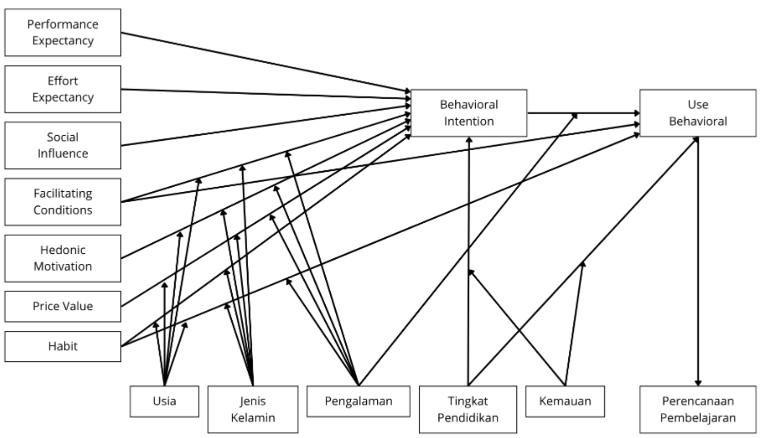

Figure 2. Conceptual Framework

**Hypothesis Development**

The hypothesis development is based on the conceptual framework in Figure 2. The following hypotheses are based on this conceptual framework:

H1. Performance Expectancy influences Behavioral Intention in using AI for learning planning.
H2. Facilitating Conditions influences Behavioral Intention in using AI for learning planning.
H3. Facilitating Conditions influences Use Behavior in using AI for learning planning.
H4. Habit influences Use Behavior in using AI for learning planning.
H5. Behavioral Intention influences Use Behavior in using AI for learning planning.
H6. Learning Planning influences Use Behavior in using AI.
H7. Willingness influences Behavioral Intention in using AI.
H8. Age moderates the influence of Behavioral Intention on Use Behavior.
H9. Gender moderates the influence of Behavioral Intention on Use Behavior.
H10. Experience moderates the influence of Behavioral Intention on Use Behavior.
H11. Education level moderates the influence of Behavioral Intention on Use Behavior.
H12. Willingness moderates the influence of Behavioral Intention on Use Behavior.

**Data Collection**

The data used in this research is primary data with data collection methods using questionnaires containing questions based on variables from the UTAUT2 model, namely performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), price value (PV), habit (H), behavioral intention (BI), and use behavior (UB) (Azizi et al., 2020; Rudhumbu, 2022; Viswanath Venkatesh, 2012). This research uses a 5-point Likert scale measurement: (1) Strongly Disagree, (2) Disagree, (3) Neutral, (4) Agree, and (5) Strongly Agree. Questionnaires were distributed in paper form directly to respondents. Questionnaire distribution was conducted over four days during the academic year, starting on Wednesday, May 28, and continuing from June 2 to 4, 2025.

**Data Analysis and Processing**

Data analysis and processing obtained from questionnaires used Structural Equation Modeling (SEM) testing. To test the data in this research, SmartPLS 4 data processing application was used. Data obtained from questionnaire distribution were analyzed to test the validity and reliability of instruments. Validity testing was conducted by evaluating the outer loading value of each indicator against the measured construct to ensure that each indicator has a significant contribution to the latent construct. Meanwhile, reliability testing was conducted by considering composite reliability values, which are used to measure the overall internal consistency of constructs. Furthermore, construct reliability analysis and convergent validity were strengthened through evaluation of several statistical indicators: Cronbach's Alpha, rho_A (alternative composite reliability), rho_C (standard composite reliability), and Average Variance Extracted (AVE). Each indicator provides information about the reliability and ability of constructs to explain the variance of their indicators. Additionally, to obtain a visual representation of inter-construct relationships in the structural model, a path diagram generated through SmartPLS software was displayed (Hair, 2021). The number of respondents needed in this research was determined based on Krejcie et al. (1996) table, totaling 92 respondents from 121 active teachers as samples in this research. The sampling method used was purposive sampling, which is a sample determination technique with certain considerations, in this case, teachers who actively teach and are relevant to learning technology integration in SMK. This technique is commonly used in SEM-based quantitative research, especially when subjects have specific characteristics that support structural modeling (Asrulla et al., 2023; Etikan, 2016).

**RESULTS AND DISCUSSION**

**Validity Test**

Model fit testing began with validity testing, which was conducted to assess the extent to which empirical evidence and theoretical arguments support the compatibility and adequacy of conclusions and actions based on experimental results and assessment methods (Tanaka et al., 2022) by calculating outer loadings values. Outer loadings values are declared valid if they are greater than or equal to ≥ 0.70 (Hair, 2021; Kusumaningrini & Sudibjo, 2021). The results of the validity test can be seen in Figure 3 below:

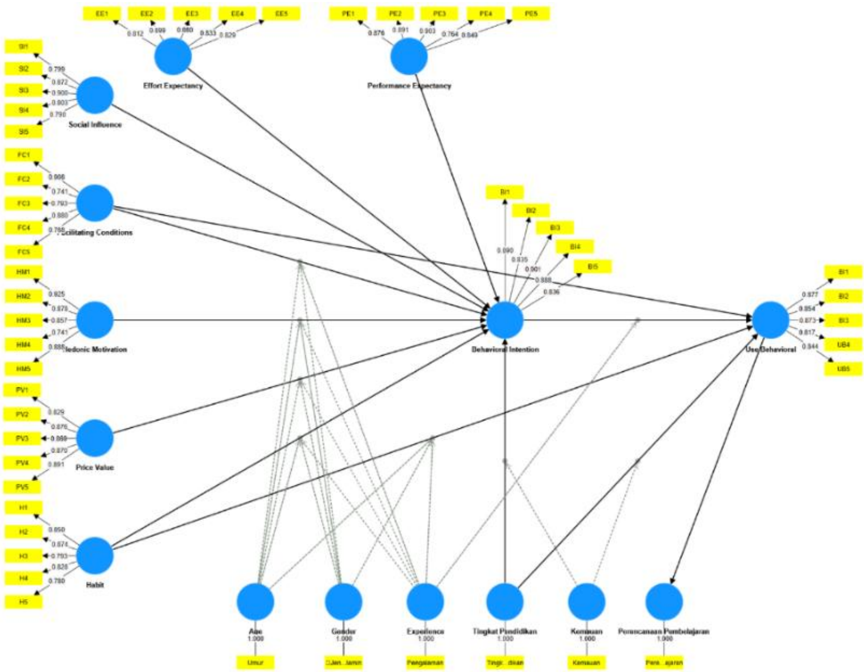

Figure 3. Validity Test

The convergent validity test results show that all indicators in each variable have loading factor values ≥ 0.70. This indicates that each indicator has a significant contribution in measuring the intended construct. In other words, these indicators are able to represent latent variables accurately and consistently. Therefore, all constructs can be declared valid and meet the requirements to proceed to the next stage of structural modeling analysis (Galantry & Tanaamah, 2024).

**Reliability Test**

Reliability testing was conducted to determine the extent to which variable measurements provide stable and consistent results (Tanaka et al., 2022). A variable is considered reliable if tested based on composite reliability with a value ≥ 0.70 (Hayadi Akbar, 2020). The reliability test results can be seen in Table 1 below:

Table 1. Reliability Test

| Variable | Composite reliability | Status |
|---|---|---|
| Behavioral Intention | 0.922 | Reliabel |
| Effort Expectancy | 0.915 | Reliabel |
| Facilitating Conditions | 0.883 | Reliabel |
| Habit | 0.890 | Reliabel |
| Hedonic Motivation | 0.929 | Reliabel |

| | | |
|---|---|---|
| Performance Expectancy | 0.915 | Reliabel |
| Price Value | 0.923 | Reliabel |
| Social Influence | 0.896 | Reliabel |
| Use Behavioral | 0.912 | Reliabel |

Based on Table 1, all variables have composite reliability values ≥ 0.70, reflecting strong internal consistency among indicators in measuring their respective constructs. This shows that all statement items in each variable are able to represent constructs consistently and stably. With the fulfillment of these reliability criteria, all variables are declared to meet the requirements for further analysis in the structural model testing stage (Galantry & Tanaamah, 2024).

**Construct Reliability and Validity**

Table 2. Construct Reliability and Validity

| | Cronbach's alpha | Composite reliability (rho_a) | Composite reliability (rho_c) | Average variance extracted (AVE) |
|---|---|---|---|---|
| Behavioral Intention | 0.920 | 0.922 | 0.940 | 0.758 |
| Effort Expectancy | 0.905 | 0.915 | 0.929 | 0.725 |
| Facilitating Conditions | 0.877 | 0.883 | 0.911 | 0.673 |
| Habit | 0.883 | 0.890 | 0.914 | 0.682 |
| Hedonic Motivation | 0.912 | 0.929 | 0.934 | 0.740 |
| Performance Expectancy | 0.910 | 0.915 | 0.933 | 0.736 |
| Price Value | 0.918 | 0.923 | 0.938 | 0.753 |
| Social Influence | 0.890 | 0.896 | 0.919 | 0.695 |
| Use Behavioral | 0.907 | 0.912 | 0.931 | 0.728 |

Table 2 presents the results of construct reliability and validity testing in the PLS-SEM model. Cronbach's Alpha values range from 0.877 to 0.920, indicating that all constructs have high internal consistency. Composite Reliability (CR) values are also above 0.90 for all constructs, indicating very good composite reliability (Hair, 2021). From the convergent validity perspective, all constructs recorded Average Variance Extracted (AVE) values above 0.50, in accordance with standards (Fornell & Larcker, David, 1981). The highest AVE value was found in the Behavioral Intention construct (0.758), while the lowest was in Facilitating Conditions (0.673), but still meets the minimum threshold. Thus, based on the table display, all constructs have met the reliability and convergent validity requirements.

**PLS-SEM Graph**

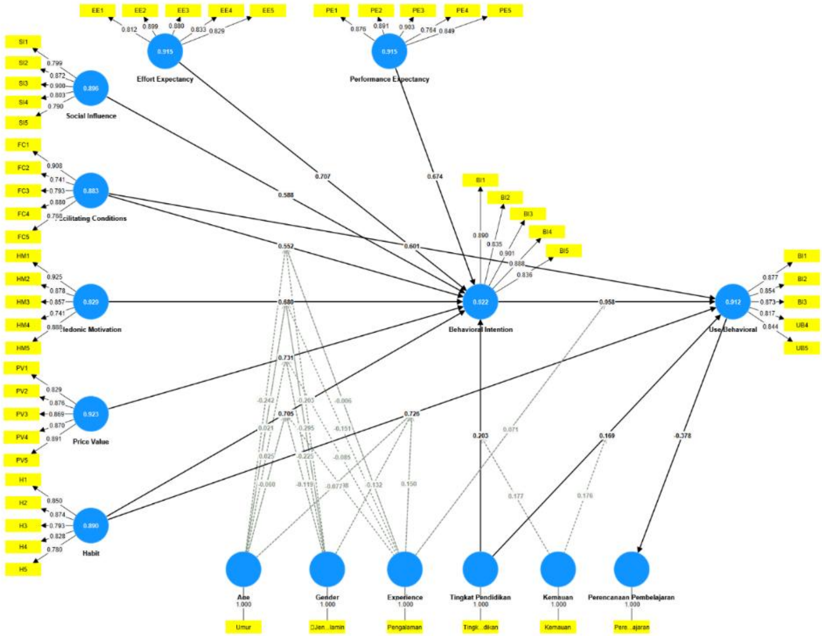

Figure 4. PLS-SEM Graph

The Partial Least Squares Structural Equation Modeling (PLS-SEM) based structural model in Figure 4 used in this research illustrates the relationships among latent constructs within the UTAUT2 framework. Exogenous constructs such as Price Value, Performance Expectancy, and Hedonic Motivation proved to be main predictors of Behavioral Intention, with coefficients of 0.726, 0.674, and 0.601, respectively. Meanwhile, Facilitating Conditions and Social Influence have lower influence (< 0.60). Behavioral Intention significantly influences Use Behavior with a very high path coefficient (0.958), strengthening the UTAUT2 postulate that intention is the main determinant of actual behavior (Viswanath Venkatesh, 2012). In this context, Behavioral Intention specifically refers to individuals' tendency to utilize Generative AI-based learning technology, such as the use of AI chatbots, automatic evaluation systems, or AI-based writing agents, which are now increasingly integrated into digital teaching and learning processes. This intention reflects strategic adoption of generative AI tools as part of modern learning transformation that is personal, adaptive, and efficient. Additional variables such as age, gender, experience, education, willingness, and learning planning were examined as moderators, but their contribution to the main path was not statistically significant (coefficient < 0.20). All constructs show very good reliability with Composite Reliability values > 0.88, indicating internal consistency and measurement stability (Hair, 2021). These findings confirm that value perception, performance expectancy, and hedonic motivation are key determinants in forming learning technology usage intentions.

**Discussion**

Based on the discussion of path analysis results in Figure 4 using SEM-PLS, it was found that the variable with the strongest influence on Use Behavior is Behavioral Intention, with a coefficient value of β = 0.958. This shows that teachers' intention to use generative AI in learning planning directly drives actual behavior in using this technology. This finding supports UTAUT theory and previous research stating that intention is the most direct predictor of behavior (Viswanath Venkatesh, Michael G. Morris, 2003; Viswanath Venkatesh, 2012). Furthermore, Hedonic Motivation provides significant influence on Behavioral Intention (β = 0.680), indicating that pleasure and satisfaction in using generative AI become teachers' main motivation in planning technology-based learning. This is consistent with findings by Hair (2021), which state that hedonic motivation plays a very important role in forming intentions to use new technology, especially in voluntary adoption contexts. Habit also shows strong influence on Behavioral Intention (β = 0.552), indicating that teachers' habits in using technology routinely become driving factors in increasing intentions to use generative AI. This habit develops from previous experience and plays a role in strengthening technology adoption (Viswanath Venkatesh, 2012).

Subsequently, the Price Value construct has a positive effect on Behavioral Intention ($\beta = 0.501$). This shows that teachers' perception of benefits obtained compared to efforts and costs incurred influences their desire to use generative AI. If teachers assess that AI provides efficiency and added value in designing learning, then their usage intention increases. Furthermore, Performance Expectancy ($\beta = 0.707$) and Effort Expectancy ($\beta = 0.588$) each show strong positive influence on Behavioral Intention. This means that teachers' belief that AI can improve their performance, as well as ease of use, play important roles in forming usage intentions (Adaptability, 2025; Moradi, 2025).

However, an interesting finding emerges in the Learning Planning variable, which actually has a negative influence on Use Behavior ($\beta = -0.378$). This indicates that learning plans that are too rigid, bureaucratic, or inflexible can become barriers to AI use. Teachers who are too bound by certain planning formats or standards tend to have difficulty integrating AI into the learning process. This finding is consistent with the opinion of Ertmer & Ottenbreit- (2010), which states that pedagogical readiness and curriculum flexibility greatly influence technology integration in education. Constructs such as Facilitating Conditions and Social Influence also contribute, although their coefficient values are lower compared to other main constructs.

factors in the context of SMK teachers who already have high intentions in using technology. This phenomenon can be interpreted as the possibility that teachers with very structured and conventional learning planning may be less flexible in integrating technology into their learning processes. Therefore, interventions in the form of teacher training should not only focus on technical aspects but also on technology-based learning design, such as technological pedagogical content knowledge (TPACK). Additionally, educational policies also need to encourage flexibility in planning so that teachers can be more adaptive to continuously developing digital technology (Chatmaneerungcharoen, 2025).

## CONCLUSION

This research aims to examine factors that influence teachers' intentions and behavior in using artificial intelligence (AI) technology, particularly generative AI, in learning planning, referring to the modified UTAUT2 theoretical framework. Based on structural model analysis results using SEM-PLS, it was found that the Behavioral Intention construct has the strongest influence on Use Behavior in generative AI use by SMK teachers in learning planning ($\beta = 0.958$). Factors such as Hedonic Motivation, Habit, Price Value, Performance Expectancy, and Effort Expectancy also contribute significantly in forming AI usage intentions, showing the importance of enjoyable experience aspects, habits, benefit perception, and technology ease. An interesting finding emerged in Learning Planning, which negatively influences usage behavior ($\beta = -0.378$), indicating that overly rigid planning structures can hinder AI integration in teaching practice. Meanwhile, moderating variables such as age, gender, experience, education, and willingness do not provide significant influence. Overall, successful AI adoption by teachers is greatly determined by intention, motivation, and technology benefit perception, not by demographic characteristics. Therefore, teacher training and educational policies need to be focused on strengthening motivation, improving positive experiences, and flexibility in technology-based learning planning.

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