Jurnal Teknik Informatika (JUTIF)
P-ISSN: 2723-3863
E-ISSN: 2723-3871
Vol. 6, No. 5, October 2025, Page. 3468-3480
https://jutif.if.unsoed.ac.id
DOI: https://doi.org/10.52436/1.jutif.2025.6.5.4940

Analysis of Technology Adoption Factors in Learning among Vocational Students using UTAUT2 Model

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Received : Jun 23, 2025; Revised : Jul 9, 2025; Accepted : Jul 9, 2025; Published : Oct 16, 2025

Abstract

Technology acceptance in vocational education is a key factor in supporting the effectiveness of teaching and learning processes in the digital era. This study aims to analyze the factors influencing technology acceptance among students of the Computer and Network Engineering (TKJ) Department at SMK Ma'arif 1 Kroya using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework. The model includes the variables Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Habit, Behavioral Intention, and Actual Usage. The results reveal that five key variables—Performance Expectancy, Effort Expectancy, Social Influence, Hedonic Motivation, and Price Value—significantly influence Behavioral Intention, while Habit, Facilitating Conditions, and Behavioral Intention directly affect Actual Usage. All constructs in the model meet validity and reliability criteria, and no multicollinearity was detected (VIF < 3.3). The coefficient of determination (R^2) values of 0.612 for Behavioral Intention and 0.673 for Actual Usage indicate strong predictive power of the model. These findings confirm the relevance of the UTAUT2 framework for understanding and enhancing technology acceptance in vocational education settings and provide valuable insights for improving technology integration in technical learning environments.

Keywords : *Acceptance Technology, UTAUT2, Learning Vocation, Behavioral Intention, Actual Usage.*

1. INTRODUCTION

The development of information and communication technology has significantly transformed the field of education, including vocational education. In the digital era, the use of technology in teaching and learning has become inevitable and is considered essential for equipping students with competencies aligned with the demands of Industry 4.0 [1]. This is particularly relevant in the Computer and Network Engineering (TKJ) department, where students are expected not only to possess technical knowledge but also to adapt to various technology-based tools and systems in their learning process. Although educational institutions have invested substantially in technological infrastructure and devices, the adoption and effective utilization of these technologies by students are still suboptimal. Previous studies have shown that the success of technology integration in education heavily depends on the level of technology acceptance among end-users, in this case, the students [2]. Therefore, understanding the factors influencing students' acceptance of technology is crucial to ensuring its effective and sustainable implementation.

Several technology acceptance models have been widely used in prior studies, such as the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) [3]. However, these models have limitations in capturing motivational dimensions and habitual use of technology, especially within the context of the digital-native student generation. To address these limitations, Venkatesh et al. (2012) developed the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), which integrates additional variables such as Hedonic Motivation, Price Value, and Habit into the analysis of

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technology acceptance [4]. The UTAUT2 framework is considered more comprehensive and appropriate for studying students in vocational high schools (SMK), who are active technology users yet influenced by social factors, habits, and personal motivation.

In the context of TKJ learning at SMK Ma'arif 1 Kroya, there has been limited research examining in depth the driving and inhibiting factors of technology acceptance from the students' perspective. This study aims to fill this gap by analyzing the influence of variables in the UTAUT2 model—namely, Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, and Habit—on students' Behavioral Intention and Actual Usage of learning technologies. Additionally, the study explores the mediating and direct relationships between these variables in shaping students' technology adoption behavior.

This research is expected to contribute empirically to understanding the dynamics of technology acceptance in vocational education and to serve as a basis for developing strategies to enhance the effective and sustainable adoption of learning technologies. Although technology has become an integral part of vocational education, its implementation is not always accompanied by high levels of student acceptance. This highlights the need for further investigation into the factors influencing students' intentions and behaviors in adopting learning technologies, particularly in the TKJ department. Based on the aforementioned background, the research question formulated in this study is: What factors in the UTAUT2 model influence the behavioral intention and actual usage of learning technologies among TKJ students at SMK Ma'arif 1 Kroya?

Accordingly, the main objective of this study is to analyze the influence of UTAUT2 variables on students' acceptance of learning technologies, with a specific focus on the relationships among Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Habit, Behavioral Intention, and Actual Usage. Furthermore, the study seeks to identify mediating effects and direct relationships between these variables in shaping students' technology adoption behavior. The findings are expected to inform strategies for enhancing technology adoption in vocational education settings effectively.

2. METHOD

2.1. Literature

The use of technology in education has grown significantly over the past two decades. Technology now functions not only as a tool to support learning but also as a medium that shapes how students learn, interact, and develop their digital skills [5]. In the context of vocational high schools (SMK), particularly within the Computer and Network Engineering (TKJ) department, the adoption of technology is crucial because it aligns with the technical competencies required in today's industrial world [6]. However, the success of technology use in learning is highly dependent on students' acceptance of the technologies employed. Various models have been proposed to explain the factors influencing technology acceptance, one of the most prominent being the Technology Acceptance Model (TAM) developed by Davis (1989). TAM highlights two key factors—Perceived Usefulness and Perceived Ease of Use—that influence users' intentions to adopt technology [7], [8]. Similarly, the Theory of Planned Behavior (TPB) has also been widely used, focusing on attitudes, subjective norms, and perceived behavioral control as predictors of behavioral intention [9]. Although these models provide a solid foundation, they are considered insufficient to fully explain motivational aspects and long-term behavioral patterns, particularly among younger users such as vocational school students.

To address these gaps, Venkatesh et al. (2012) proposed the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). This extended model incorporates additional variables—such as Hedonic Motivation, Price Value, and Habit—into the analysis framework, making it more comprehensive for studying technology acceptance in various contexts, including education [10].

P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
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UTAUT2 is regarded as more relevant for investigating technology adoption among the digital generation because it accounts for emotional and habitual aspects of technology use. The Performance Expectancy (PE) variable in UTAUT2 refers to the belief that using technology will enhance learning outcomes or productivity. In an educational context, PE relates to students' perceptions that technology helps them understand material more effectively or complete tasks more efficiently [11]. Effort Expectancy (EE), on the other hand, reflects the perceived ease of use of a system or learning application, which influences students' comfort with accessing and regularly using technology [12].

Social Influence (SI) also plays a vital role in education, as students' decisions regarding technology use are often shaped by peers, teachers, or even parents [13]. Facilitating Conditions (FC) describe the degree to which students perceive that adequate infrastructure and technical support are available to enable effective technology use. Previous studies have demonstrated that FC directly influences actual usage, as perceptions of technical support can determine users' comfort and confidence in using technology [1]. Additional variables in UTAUT2, such as Hedonic Motivation (HM), highlight the importance of enjoyment or pleasure derived from using technology. Among students, intrinsic motivation and positive experiences with technology can significantly enhance engagement and learning [14]–[16]. Price Value (PV), though commonly studied in consumer contexts, remains relevant in education because students may evaluate the costs of technology use, including access fees, internet data, or time invested [17]. Meanwhile, Habit (HB) reflects the tendency to engage in repeated technology use, which over time can become a consistent behavior even without explicit intention [18].

Previous research applying UTAUT2 in educational settings has reported varying findings depending on cultural context, educational level, and the specific technologies examined [19]. Nevertheless, Behavioral Intention (BI) consistently emerges as a central mediator between external factors and actual usage (AU). Adapting this model to the context of TKJ students in vocational schools is expected to yield deeper insights into the factors driving technology acceptance in practice-oriented, technology-intensive learning environments.

2.2. Hypothesis

H1: Performance Expectancy positively affects Behavioral Intention

Performance Expectancy (PE) refers to the degree to which an individual believes that using a particular technology will help achieve desired outcomes, such as improved academic performance. In the context of TKJ students, PE manifests as the belief that learning technologies can help them understand material more quickly, improve task efficiency, and provide access to broader learning resources [20]. Students who perceive direct benefits from technology use are more likely to develop a strong intention to continue using it in their learning process.

Previous studies have identified PE as one of the strongest predictors of Behavioral Intention across various contexts, including digital education [21]. Therefore, students' understanding of how technology supports their academic success becomes a key factor in fostering their acceptance. Thus, the higher students perceive the utility of technology, the greater their likelihood of intending to use it consistently.

H2: Effort Expectancy positively affects Behavioral Intention

Effort Expectancy (EE) reflects the perceived ease of using a particular technology. In vocational school settings, where students' digital skills vary widely, the ease of using learning systems or applications becomes a crucial factor. When students find technology intuitive, uncomplicated, and requiring minimal effort to learn, they are more likely to develop a positive intention to use it regularly [22].

Previous research has shown that perceived ease of use consistently influences users' intentions to adopt new systems, particularly among students [23]. In this context, students' initial experience with

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technology, user-friendly interfaces, and instructional support from teachers shape their perception of ease. Therefore, EE is expected to have a positive effect on Behavioral Intention in this study.

H3: Social Influence positively affects Behavioral Intention

Social Influence (SI) refers to an individual's perception that important others—such as peers, teachers, or family members—believe they should use a particular technology. Among vocational school students, social factors play a significant role, as adolescents are often influenced by their environment, including attitudes toward learning technologies [13]. When students observe that their friends or teachers actively use and support technology, they are more inclined to follow suit.

Several studies have demonstrated that SI is particularly influential during the initial stages of technology adoption, especially in group or classroom settings [24]. The influence of authority figures, such as teachers or class leaders, can serve as a powerful trigger for students to form an intention to use technology. Therefore, SI is hypothesized to directly contribute to students' intention to adopt learning technologies.

H4: Facilitating Conditions positively affect Actual Usage

Facilitating Conditions (FC) refer to the extent to which individuals perceive that the necessary infrastructure and resources are available to support their technology use. In educational environments, FC includes the availability of hardware (e.g., computers or laptops), a stable internet connection, and technical support from teachers or IT staff [25]. When students perceive that all prerequisites for technology use are met, they are more likely to use the technology in practice.

Previous studies have confirmed that FC has a direct relationship with actual usage, particularly when users' intentions have already formed [26]. In vocational school contexts, students are more confident in using technology when they feel they will not encounter technical obstacles. Thus, FC is not merely a supporting factor but can also be a main determinant of sustainable technology use.

H5: Hedonic Motivation mediates the relationship between Effort Expectancy and Behavioral Intention

Hedonic Motivation (HM) refers to the enjoyment or pleasure experienced when using technology. For TKJ students, HM may include enjoyable experiences when learning with interactive media, network simulation visualizations, or dynamic learning platforms. When students feel comfortable and enjoy using technology because it is easy to use (Effort Expectancy), they develop intrinsic motivation to continue using it [27].

Previous studies have found that HM strongly mediates the relationship between EE and Behavioral Intention, particularly among younger users whose emotional experiences with technology are highly influential [28]. When ease of use enhances the enjoyment of learning, the intention to use technology sustainably also increases. Therefore, HM plays an important role in bridging the effect of EE on BI.

H6: Price Value positively affects Behavioral Intention

Price Value (PV) reflects students' assessment of the trade-off between the benefits of using technology and the associated 'costs', whether financial, time, or effort. Although learning technologies are often provided free of charge by schools, students still consider factors such as internet data costs, additional time, or personal expenses to access these technologies. When they perceive that the benefits outweigh the sacrifices, their intention to use the technology increases.

Previous studies have shown that PV significantly influences BI in digital technology contexts, especially among students from lower to middle socioeconomic backgrounds. Thus, a positive perception of the value of technology can strengthen students' intention to continue using it, despite access challenges or resource constraints.

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H7: Habit directly affects Actual Usage

Habit (HB) describes the tendency of users to perform actions automatically due to established routines. Among TKJ students, using learning technologies can become habitual when practiced routinely, such as accessing an online learning platform daily or completing assignments through digital applications. Over time, this habit develops and encourages students to use technology even without conscious deliberation.

Previous studies have found that HB has a direct and significant effect on actual technology use, especially when users have become accustomed to and comfortable with the system. Therefore, in this model, HB is positioned as a direct predictor of Actual Usage, independent of intention or other motivational factors.

H8: Behavioral Intention positively affects Actual Usage

Behavioral Intention (BI) reflects an individual's willingness or tendency to use technology in the future. In many behavioral theories, including UTAUT2, BI is considered the primary determinant of actual behavior, as strong intentions typically lead to real actions. For TKJ students, the intention to use learning technology may manifest as tangible activities, such as logging into an LMS, completing online quizzes, or participating in virtual training.

Several studies have confirmed the strong connection between BI and Actual Usage, particularly in technology-based educational settings. Therefore, BI is viewed as the variable that bridges psychological and environmental factors with users' actual behaviors. Accordingly, the stronger the students' intention, the more likely they are to use technology routinely in their learning process.

2.3. Types and Approaches Study

Study This is study quantitative explanatory with approach survey. The purpose is For test influence various factor in the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model towards intention and behavior student in use technology learning. Approach This chosen Because capable measure connection between variable in a way statistics and explain how much big influence variable independent to variable dependent.

UTAUT2 model is used as runway theoretical for to design framework conceptual and hypothetical research. Research this is also of a nature correlational, because to browse connection between variables such as Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Habit, Behavioral Intention, and Actual Usage.

Study implemented at SMK Ma'arif 1 Kroya, which is school vocation with concentration Computer and Network Engineering (TKJ) expertise. School This chosen Because has implement learning based on technology and have adequate digital infrastructure. Population in study This is all over student class XI and XII TKJ expertise program in the year teachings walking. Selection population This based on assumptions that students at the level This has own enough experience in use technology learning.

2.4. Research Method

Sample taken use probability sampling technique with simple random sampling approach. The number of sample counted use formula slovin:

$$n = \frac{N}{1+N(e)^2} \tag{1}$$

With:

- n = size sample
- N = total population TKJ students
- e = margin of error (5%)

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For example If amount population is 200 students, then size sample taken is:

$$n = \frac{200}{1 + 200(0.05)^2} = \frac{200}{1 + 0.5} = 133.33 \Rightarrow\approx 133 \text{ responden}$$

2.5. Data collection technique

Data collected use questionnaire closed based on 5- point Likert scale (1 = very much disagree) agree, 5 = strongly agree). Instrument questionnaire developed based on indicators from every variable in the UTAUT2 model. Before distribution, instruments tested validity and reliability through trial limited (pilot test).

Distribution questionnaire done online via Google Forms, as well as in a way directly in class for students who do not own internet access stable. This is done for ensure representativeness and completeness of data.

2.6. Analysis Techniques

Data analyzed use Structural Equation Modeling – Partial Least Squares (SEM-PLS) approach through device soft SmartPLS 4. Reasons SEM-PLS selection is his ability in handle models with Lots latent constructs, non-normal data, as well amount relative sample in progress. Analysis done through two stage main:

1) Measurement Model Testing (Outer Model): Validity test indicator (loading factor > 0.7), reliability construct (Cronbach's Alpha and Composite Reliability > 0.7), and validity discriminant (AVE > 0.5) [29] .
2) Structural Model Testing (Inner Model): Significance test connection between construct done through t-statistic value (>1.96) and p-value (<0.05) using bootstrapping method. In addition that, value coefficient determination (R^2) and predictive relevance (Q^2) are also used For evaluate model strength [30] .

2.7. Instrument Study

Instrument study arranged based on constructs and indicators that have been adapted from the UTAUT2 model by Venkatesh et al. (2012), with modification in accordance context learning vocation. Every construct represented by three statement items that are measured use Likert scale 1–5 (1 = very much disagree, 5 = strongly agree). Item selection is done for ensure that every aspect theoretical from each construct can measured in a way direct through perception respondents.

Table 1. Research instruments /items

No.	Variables / Constructs	Item Code	Statement
1	Performance Expectancy (PE)	PE1	Technology help I finish task Study more fast
		PE2	Technology create a learning process I more effective
		PE3	Use technology increase productivity Study I
2	Effort Expectancy (EE)	EE1	Technology used Enough easy studied
		EE2	I'm fast used to use technology in learning
		EE3	Interaction with system technology learning Enough clear and easy
3	Social Influence (SI)	SI1	Friend I push I For use technology

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		SI2	My teacher support use technology in learning
		SI3	People around consider I should use technology
4	Facilitating Conditions (FC)	FC1	I have access to device the technology needed
		FC2	I have knowledge technical For use technology learning
		FC3	I know where to go request help If experience constraint technical
5	Hedonic Motivation (HM)	HM1	I feel like use technology in Study
		HM2	Learning with technology feel pleasant
		HM3	I enjoy the learning process use technology
6	Price Value (PV)	PV1	Benefit technology comparable with the effort that I take it out
		PV2	I feel use technology No throw away time
		PV3	I get more Lots profit compared to the loss
7	Habit (HB)	HB1	I'm used to it use technology in activity Study
		HB2	I use technology almost every day For Study
		HB3	Use technology Already become part from habit I
8	Behavioral Intention (BI)	BI1	I intend use technology in learning to front
		BI2	If available , I will use technology For Study
		BI3	I have desire strong For use technology learning
9	Actual Usage (AU)	AU1	I really use technology moment Study
		AU2	I use technology For do tasks school
		AU3	I take advantage of technology in accordance need in the learning process

Use three items for each construct aiming For increase internal reliability, as well as make it easier testing validity construct through the measurement model (outer model). Instrument This designed for easy understood by vocational school students, with clear and contextual language , so capable produce accurate and representative data condition Actually in reception technology learning .

2.8. Variance Inflation Factor

In quantitative research using the Structural Equation Modeling–Partial Least Squares (SEM-PLS) approach, it is essential to ensure that multicollinearity does not occur among the latent constructs. Multicollinearity arises when two or more independent variables in the model are highly correlated, which can distort the estimation of path coefficients and obscure the interpretation of relationships between variables [31]. To detect multicollinearity in this model, the Variance Inflation Factor (VIF) test is conducted. The VIF indicates the extent to which a construct is influenced by other constructs. Generally, a VIF value ≤ 5 is considered acceptable; however, a more conservative standard for SEM-PLS models recommends a VIF ≤ 3.3 [32].

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Table 2. Latent VIF test results

Latent Construct	VIF Value
Performance Expectancy (PE)	2.87
Effort Expectancy (EE)	2.45
Social Influence (SI)	2.31
Facilitating Conditions (FC)	1.76
Hedonic Motivation (HM)	2.15
Price Value (PV)	1.83
Habit (HB)	1.52

Based on the data analysis results using SmartPLS 4, all latent constructs in this study have VIF values below 3.3. This indicates that no multicollinearity exists among the constructs in the structural model. The highest VIF was observed for the Performance Expectancy construct at 2.87, while the lowest was found for the Habit construct at 1.52. Therefore, it can be concluded that the research model has passed the multicollinearity test, and each independent variable in the model makes a unique contribution to the dependent variables being analyzed. This ensures that the structural parameter estimates in the model are valid and not distorted by excessively strong inter-variable relationships.

3. RESULT

3.1. Data Collection Results

Data collection was carried out through distribution questionnaire to student class XI and XII majoring in Computer and Network Engineering (TKJ) at SMK Ma'arif 1 Kroya. Total respondents who successfully collected as many as 133 students, all of whom provide complete and proper data For analyzed more continue. Questionnaire spread out in online and offline forms for accommodate all over student in a way evenly. Profile Respondent classified based on characteristics demographic main ones include type gender, level class, and frequency use technology daily. The table below This show summary characteristics respondents involved in study.

Table 3. Latent VIF test results

No.	Characteristics	Category
1	Type Sex	Male : 78 (58.6%) Female: 55 (41.4%)
2	Class	XI: 65 (48.9%) XII: 68 (51.1%)
3	Frequency Use Technology Daily	1–2 hours: 40 (30.1%) 3–4 hours: 55 (41.4%) >4 hours: 38 (28.5%)

Most of the Respondent in study This is student man as many as 78 people (58.6%), while student Woman totaling 55 people (41.4%). Composition This reflect domination student common man found in the TKJ department. Based on level class, there are 65 students class XI (48.9%) and 68 students class XII (51.1%), which shows sufficient distribution evenly between level. From the side frequency use technology daily, majority student use technology for 3–4 hours per day (41.4%), followed by students who use more of 4 hours per day (28.5%) and those who use 1–2 hours per day (30.1%). This is show

P-ISSN: 2723-3863
https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871
DOI: https://doi.org/10.52436/1.jutif.2025.6.5.4940

that part big student own habit interact with technology in quite a long duration , so that Enough relevant For measure reception technology in a way actual.

3.2. Measurement Model Test Results (Outer Model)

Measurement model testing done For evaluate validity convergent, validity discriminant, and reliability latent constructs in the UTAUT2 model. Validity test results convergent shown in Table 4, which presents Average Variance Extracted (AVE) value for each construct. Based on results said, all construct own AVE value above 0.5, with mark highest found in Behavioral Intention (0.769) and value lowest in Effort Expectancy (0.684). This is show that every construct own adequate capability in explain Variance the indicators that make it up, so validity convergent can stated fulfilled.

Table 4. Convergent Validity test results

No.	Latent Construct	AVE	Information
1	Performance Expectancy	721	Valid
2	Effort Expectancy	684	Valid
3	Social Influence	693	Valid
4	Facilitating Conditions	707	Valid
5	Hedonic Motivation	755	Valid
6	Price Value	698	Valid
7	Habits	734	Valid
8	Behavioral Intention	769	Valid
9	Actual Usage	742	Valid

Next, validity discriminant tested use approach Fornell-Larcker Criterion, as shown in Table 5. Validity discriminant considered fulfilled if mark root AVE square of each construct more tall than correlation between construct. The results show that all diagonal value (marked in table as mark highest per row) more big than correlation other in the same column. As example, value The AVE root for Performance Expectancy is 0.849, which is more big from the correlation with other constructs such as Effort Expectancy (0.621) and Social Influence (0.541). This prove that construct in a mutual model independent One each other and not experience overlap measurement, so that validity discriminant stated fulfilled.

Table 5. Results of the Discriminant Validity test

Construct	PE	EE	SI	FC	HM	PV	HB	BI	AU
Performance Expectancy	0.849								
Effort Expectancy	0.621	0.827							
Social Influence	0.541	0.574	0.832						
Facilitating Conditions	0.498	0.526	0.493	0.841					
Hedonic Motivation	0.612	0.644	0.537	0.503	0.869				
Price Value	0.589	0.621	0.507	0.494	0.615	0.835			
Habits	0.501	0.564	0.478	0.586	0.578	0.559	0.857		
Behavioral Intention	0.654	0.672	0.628	0.524	0.693	0.601	0.634	0.877	
Actual Usage	0.544	0.582	0.488	0.608	0.569	0.538	0.698	0.702	0.861

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Construct reliability was assessed using two key indicators: Cronbach's Alpha and Composite Reliability (CR), as presented in Table 6. All constructs exhibit Cronbach's Alpha values above 0.7, with the highest values observed for Behavioral Intention (0.841) and Actual Usage (0.833). The Composite Reliability values also exceed the minimum threshold of 0.7, indicating very good internal consistency among the indicators within each construct. Therefore, it can be concluded that all constructs in this model demonstrate strong reliability and can be considered dependable in measuring the intended concepts.

Table 6. Construct Reliability Test Results

No.	Latent Construct	Cronbach's Alpha	Composite Reliability (CR)	Information
1	Performance Expectancy	0.814	0.884	Reliable
2	Effort Expectancy	0.796	0.869	Reliable
3	Social Influence	0.762	0.847	Reliable
4	Facilitating Conditions	0.778	0.864	Reliable
5	Hedonic Motivation	0.829	0.899	Reliable
6	Price Value	0.781	0.860	Reliable
7	Habits	0.812	0.886	Reliable
8	Behavioral Intention	0.841	0.905	Reliable
9	Actual Usage	0.833	0.891	Reliable

3.3. Structural Model Test Results (Inner Model)

After the measurement model was confirmed to be valid and reliable, the next step was to test the structural model to evaluate the relationships between latent constructs. Table 7 presents the results of the path coefficients, t-statistics, and p-values. Based on these results, all path relationships between variables in the model are statistically significant, with p-values < 0.05 and t-statistics > 1.96. The strongest path is observed between Behavioral Intention and Actual Usage (coefficient = 0.413; t = 6.214; p = 0.000), indicating that students' intention has a substantial influence on their actual use of technology in learning.

Table 7. Results of the Path Coefficient, t-Statistic, and p-Value tests

No.	Connection Between Variables	Path Coefficient	t- Statistics	p-Value	Information
1	PE → BI	0.274	3,891	0.000	Significant
2	EE → BI	0.215	2.945	0.003	Significant
3	SI → BI	0.162	2.132	0.034	Significant
4	HM → BI	0.229	3.118	0.002	Significant
5	PV → BI	0.178	2,489	0.013	Significant
6	HB → AU	0.367	5.102	0.000	Significant
7	FC → AU	0.251	3.302	0.001	Significant
8	BI → AU	0.413	6.214	0.000	Significant

Connection other significant direct covering the influence of Performance Expectancy, Effort Expectancy, Social Influence, Hedonic Motivation, and Price Value on Behavioral Intention, as well as the influence of Habit and Facilitating Conditions on Actual Usage. The coefficient values on the Habit

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→ Actual Usage (0.367) and Facilitating Conditions → Actual Usage (0.251) paths indicate that behavior habits and support infrastructure play role important in push use technology by TKJ students. This is consistent with characteristics student vocational tendencies depend on experience direct and availability source Power in adopt digital learning system.

Table 8. Results of the R^2 and Q^2 Construct Test Values Dependent

Construct Dependent	R^2	Information	Q^2	Information
Behavioral Intention	0.612	Strong	0.451	Predictive models Good
Actual Usage	0.673	Strong	0.518	Predictive models Good

For evaluate Power explore model in predict endogenous variables, used mark coefficient determination (R^2) and Q^2 value as indicator predictive relevance, as shown in Table 8. The R^2 value is 0.612 for construct Behavioral Intention and 0.673 for Actual Usage construct shows that this model capable explain Variance by 61.2% and 67.3% on each variable dependent. Besides that is, the Q^2 value for second constructs of 0.451 and 0.518 respectively, which indicates that the model has quality good and relevant prediction in a way statistics. Therefore that, can concluded that the structural model own power strong and valid predictive for explain behavior reception technology by vocational school students.

4. CONCLUSION

This study aimed to analyze the factors influencing students' acceptance of learning technologies in the Computer and Network Engineering (TKJ) Department at SMK Ma'arif 1 Kroya using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework. Based on the SEM-PLS analysis results, five main constructs—Performance Expectancy, Effort Expectancy, Social Influence, Hedonic Motivation, and Price Value—were found to have a significant influence on Behavioral Intention. This suggests that students' intention to use technology is shaped by their perceptions of its benefits, ease of use, social encouragement, enjoyment, and perceived cost-benefit trade-offs.

In addition, Behavioral Intention was shown to have a direct and significant effect on Actual Usage, indicating that the stronger the students' intention, the higher the likelihood that they will actively use technology in their learning process. These findings reinforce the theoretical foundation of the UTAUT2 framework, where intention serves as a mediating variable bridging initial perceptions of technology with actual usage behavior.

The constructs of Habit and Facilitating Conditions also demonstrated a significant direct influence on Actual Usage. Students' habitual use of technology, as well as the availability of adequate technical support and infrastructure, were identified as critical supporting factors for ensuring sustainable technology adoption. These aspects are important for schools to consider, particularly in providing sufficient facilities and fostering consistent routines for digital learning.

Overall, the findings of this study confirm that the UTAUT2 model is effective and relevant in explaining the dynamics of learning technology acceptance in vocational education settings. All constructs in the model passed validity, reliability, and multicollinearity tests, and the R^2 and Q^2 values indicate strong predictive power. These results can serve as a foundation for schools and educators to design strategies for improving technology adoption, taking into account students' motivation, comfort, and supportive learning environments.

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