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Understanding Student Acceptance of AI in Mojokerto Regency High Schools and a Framework for Effective Integration

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Abstract— Background: The use of AI in education is growing rapidly, especially in adaptive learning and automated feedback. Recent studies show widespread adoption of AI in higher education, but research at the secondary school level is limited. Factors such as ease of use, motivation, and institutional support play an important role accepting these technologies. **Objective**: The objective of this study is to investigate the acceptance and usage of the Question.AI application among high school students in Mojokerto Regency, to identify the factors that influence its adoption and effectiveness in enhancing learning outcomes. **Methods**: The methodology adopted for this research comprises a quantitative study design using a probability sampling method, specifically the Stratified Random Sampling technique. A total of 400 high school students from Mojokerto Regency participated. Data collection was conducted through structured questionnaires designed to evaluate factors influencing the adoption of the Question.AI application. **Result**: The result revealed that Facilitating Conditions (FC), Habit (H), and Hedonic Motivation (HM) significantly influence students' behavioral intention to use the Question.AI application. Among these, Habit and Hedonic Motivation showed the strongest effect, indicating that students are more likely to adopt AI tools when their use becomes routine and satisfied. **Conclusion**: These results support the UTAUT2 framework and highlight the need for enjoyable user experiences and adequate support systems to drive sustained adoption. The findings contribute to understanding AI acceptance at the secondary education level and offer practical insights for integrating AI applications more effectively into school environments.
Keywords— Artificial Intelligence; Acceptance; AI Based Learning; UTAUT2

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I. INTRODUCTION

The rapid development of technology has significantly changed the way humans interact, work, and perform daily activities. Advances in artificial intelligence (AI) are the main driver of this change. As expressed in research related to artificial intelligence [1], AI is applied in various domains such as visual and speech recognition, decision-making, inter-language translation, robotics, and others. The implementation of AI technology demonstrates its ability to simplify and accelerate human tasks. For example in education [2] [3], in visual recognition, AI-powered systems like Google Lens and facial recognition technology in security applications help automate identification processes, in speech recognition, virtual assistants such as Amazon Alexa and Google Assistant utilize AI to interpret and respond to voice commands, enhancing user experience.

AI has also made significant changes and progress in several aspects, especially in the aspect of education [4]. Based on the AI Index 2023 Annual Report by Stanford University [5] shows that 75.23% of AI publications focus on the field of education and this shows that the application of AI technology in the learning process has a crucial role. The increasing number of journal publications related to the development of AI technology indicates that every entity involved in education has high confidence in the positive potential of AI technology in shaping a better future of education. In the context of education, AI-powered automated grading systems help streamline assessments, allowing instructors to focus more on pedagogy rather than administrative tasks. In higher education, predictive analytics assist institutions in identifying at-risk students, improving retention rates through early intervention [6] [7]. Also shows that AI-driven learning analytics can help educators identify students' strengths and weaknesses, enabling timely interventions to improve learning outcomes.

However, the use of AI-based learning applications is not free from problems. Based on the results of interviews conducted with public high school students, some students revealed that there were bugs or errors when using the application. Other students also added that there was a discrepancy in the answers given between the application, book, and teacher which caused confusion. The problems experienced by students were in line with some reviews on the Google Play Store regarding their dissatisfaction in using the application. The integration of AI in education offers numerous advantages in enhancing student learning experiences, providing personalized support, and automating administrative tasks. AI-powered intelligent tutoring systems (ITS), such as Carnegie Learning and AutoTutor, have demonstrated their ability to adapt learning materials to individual student needs, significantly improving comprehension and engagement [8] Additionally, AI-based learning analytics help educators identify students at risk

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of falling behind by analyzing their learning patterns and providing tailored interventions. In higher education, These AI-powered tools analyze student data, provide customized feedback, and recommend personalized learning paths, enabling lecturers to effectively address the diverse needs of their students [9]. Moreover, AI-powered tools such as real-time language translation and speech-to-text services improve accessibility, benefiting students with disabilities or those learning in a non-native language [10]. Despite challenges such as ethical concerns and data privacy, research continues to highlight AI’s potential in transforming education by making learning more adaptive, inclusive, and efficient. As AI technology evolves, its thoughtful integration into educational systems will play a critical role in preparing students for future workforce demands and lifelong learning opportunities.

The implementation of information technology is always related to user acceptance. Previous studies have shown that technology acceptance is key to the successful implementation of information technology in educational settings. The level of user acceptance significantly influences the effectiveness and overall success of technology adoption. In particular, when considering the integration of AI tools in education, understanding the factors that shape student acceptance becomes crucial for fostering meaningful adoption and maximizing the benefits of these technologies in improving learning outcomes [11], acceptance of an information technology is the main requirement to be able to determine the level of success of the information technology implementation.

Researchers widely agree that AI technology plays a significant role in enhancing the learning process. Studies have identified several factors that influence users' adoption of AI technology in education. Using the UTAUT2 model, researchers have examined various AI-driven tools that support teaching and learning, including Chatbots [12], ChatGPT [13][14][15], Learning Management Systems (LMS) [16], Marketplaces [17], Smartwatches [18] and Google Classroom [19]. These studies highlight the diverse applications of AI in education and the factors influencing its acceptance among users.

This study aims to identify and analyze the factors influencing the acceptance and usage behavior of AI-based learning applications among high school students. Previous research has explored college students' acceptance of AI applications such as ChatGPT [20][12][21], AI Chatbot and other AI technologies in education. These studies have recommended conducting research at different levels of education to expand the scope and relevance of findings. Therefore, this research aims to fill the gap by providing insights into the acceptance of AI-based learning applications, specifically among public high school students in Mojokerto Regency.

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II. RESEARCH METHOD

The research method of this study is based on the Unified Theory of Acceptance and Use of Technology (UTAUT) and its extension, UTAUT2. Researchers widely agree that AI technology significantly enhances the learning process [22]. Studies have identified several factors influencing users' adoption of AI technology in education. Using the Unified Theory of Acceptance and Use of Technology (UTAUT) model proposed by Venkatesh, with the rapid evolution of technology and changing user behaviour, UTAUT was extended to broader contexts, particularly consumer technology [23]. In 2012, Venkatesh et al. proposed UTAUT2.

For this study, the conceptual model employed is UTAUT2 [20], adapted to examine the acceptance and usage behaviour of AI-based learning applications with ten variables: eight independent variables (Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Personal Innovativeness, Price Value, Habit, And Hedonic Motivation), one dependent variable (Use Behaviour), and one intervening variable (Behavioural Intention) [20]. A visual representation of the UTAUT2 model used in this study is provided in Figure 1.

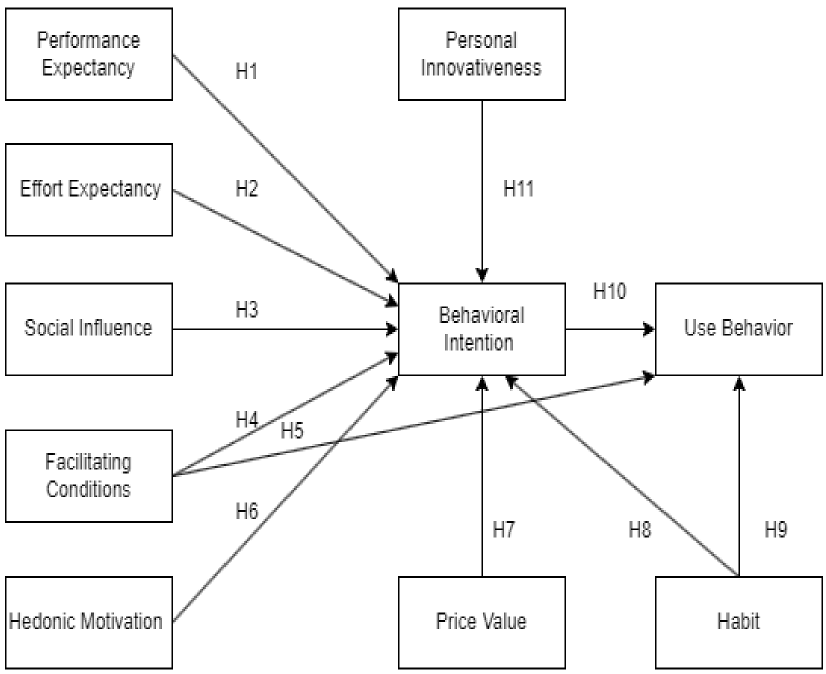

Fig 1. Research Model Hypothesis

Performance expectancy refers to how much individuals believe a system will improve their performance [24]. In education, it reflects students' belief that AI learning applications can enhance academic outcomes and learning efficiency. Thus, the hypothesis is:

H1: *Performance Expectancy has positively affect* on students' *Behavioral Intention* towards AI learning applications.

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Effort expectancy measures the perceived ease of using a system [25]. This variable refers to the user's perception of the technical skills of use and the difficulty in using the application [26]. Based on this, the hypothesis is:

H2: *Effort Expectancy* has a positive influence on students' *Behavioral Intention* towards AI learning applications.

Social influence can be defined as a person's ability to make users feel trust and confidence when having to use a product or service [27]. When a person feels positively influenced by friends or other trusted influences, students tend to be more receptive and have a stronger intention to use the application [20]. Based on this, the hypothesis is:

H3: *Social* influence has a positive influence on students' *Behavioral Intention* towards AI learning applications.

Facilitating conditions refer to the level of accessibility to resources and support needed to complete a task [28]. In learning, higher accessibility increases students' intention and usage of AI applications. Based on this, the hypotheses are:

H4: *Facilitating Conditions* has a positive influence on students' *Behavioral Intention* towards AI learning applications.

H5: *Facilitating Conditions* have a positive influence on student users' *Use Behavior* towards AI learning applications.

Hedonic motivation refers to the level of pleasure or satisfaction felt by users when using an application [29]. In learning, enjoyable user experiences enhance motivation and encourage independent study.

H6: *Hedonic Motivation* positively influences students' *Behavioral Intention* towards AI learning applications.

Price value represents the balance between perceived benefits and monetary cost [30]. If students perceive value in AI applications, they are more likely to adopt them.

H7: *Price value* positively influences students' *Behavioral Intention* towards AI learning applications.

Habit reflects the tendency to perform behaviors automatically due to prior experience [30]. Frequent usage strengthens students' intention and actual usage.

H8: *Habit* positively influences students' *Behavioral Intention* towards AI learning applications.

H9: *Habit* has a positive influence on students' *Use Behavior* towards AI learning applications.

Personal innovativeness is the willingness to adopt new technology or the tendency to try new features and advances in the IT domain [31]. Students with higher innovativeness are more likely to use AI applications

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H10: *Personal innovativeness* positively influences students' *Behavioral Intention* towards AI learning applications.

Behavioral intention reflects a user's commitment to adopting technology [32]. Strong intention leads to higher actual usage [33].

H11: *Behavioral Intention* has a positive influence on students' *Use Behavior* towards AI learning applications.

Table 1. Hypothesis

	Hypothesis
H1	*Performance Expectancy has a* positive effect on students' *Behavioral Intention* towards AI learning applications
H2	*Effort Expectancy* has a positive influence on students' *Behavioral Intention* towards AI learning applications
H3	*Social* influence has a positive influence on students' *Behavioral Intention* towards AI learning applications
H4	*Facilitating Conditions* has a positive influence on students' *Behavioral Intention* towards AI learning applications
H5	*Facilitating Conditions* have a positive influence on student users' *Use Behavior* towards AI learning applications
H6	*Hedonic Motivation* positively influences students' *Behavioral Intention* towards AI learning applications
H7	*Price value* positively influences students' *Behavioral Intention* towards AI learning applications
H8	*Habit* positively influences students' *Behavioral Intention* towards AI learning applications
H9	*Habit* has a positive influence on students' *Use Behavior* towards AI learning applications
H10	*Personal innovativeness* positively influences students' *Behavioral Intention* towards AI learning applications
H11	*Behavioral Intention* has a positive influence on students' *Use Behavior* towards AI learning applications

To effectively integrate AI into education, several key implications must be considered. Improving AI usability is essential, and developers should focus on creating user-friendly interfaces and ensuring seamless integration with existing educational platforms to enhance Effort Expectancy. Additionally, enhancing institutional support by providing technical assistance, resources, and training can strengthen Facilitating Conditions, making AI adoption more accessible for students. Encouraging social influence through peer-led AI learning communities can boost student confidence and willingness to engage with AI-powered educational tools. Furthermore, boosting motivation by incorporating gamification and interactive AI-driven content can increase Hedonic Motivation and overall engagement. Finally, balancing cost and value is crucial; offering affordable AI learning tools with clear academic benefits will enhance

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students' Price Value perception and drive higher adoption rates. Developing a robust framework for AI integration in education requires understanding how various motivational, behavioral, and environmental factors shape student adoption. The proposed UTAUT2-based model provides a structured approach to analyzing Behavioral Intention and Use Behavior toward AI learning applications. By addressing usability, accessibility, social dynamics, and engagement, educators and developers can enhance AI adoption, improve learning experiences, and better prepare students for AI-driven education.

The research was conducted by distributing questionnaires via Google Forms, with a total of 400 participants completing the survey. Incomplete or invalid responses were excluded from the final dataset. The questionnaire was designed using Google Forms with required fields to minimize missing data. This method allowed for efficient data collection, reaching a broad audience while ensuring convenience and accessibility for respondents. A pilot test was conducted to ensure the clarity and reliability of the questionnaire. Participants were recruited from high schools and were required to have used Question.AI at least once to be eligible for the study. To ensure ethical compliance, students provided informed consent before participating and data were stored securely and used solely for academic purposes. Data collection was carried out over six months, from March to August 2024. The questionnaire took an average of 30 minutes to complete, allowing students ample time to provide thoughtful responses. The study followed Slovin’s formula to determine an appropriate sample size, resulting in a target of 400 valid responses.

The research process was structured to ensure replicability. The study followed a systematic procedure, beginning with the development of the questionnaire, conducting a pilot test, and refining questions based on feedback. Participants were then recruited, given a consent form, and asked to complete the questionnaire online. The collected data was analyzed quantitatively to assess the factors influencing students' Behavioral Intention and Use Behavior toward AI learning applications. The population in the study was public high school students in Mojokerto district, Mojokerto is a city in East Java Province, Indonesia, located about 50 km southwest of Surabaya. The city has a relatively small area but plays an important role as an economic, trade and education centre in the surrounding area. Known as part of the historical region of the Majapahit Kingdom, Mojokerto has a rich cultural heritage, including archaeological sites and museums that preserve relics of the kingdom's heyday. In terms of education, Mojokerto City has a variety of educational institutions ranging from primary to high school levels, including several public high schools that serve as learning centres for the local community. The city's infrastructure also continues to develop with the support of public facilities, transportation services, and connectivity that facilitate the activities of its residents. With strong economic and historical potential, Mojokerto

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continues to develop into a thriving city while maintaining its cultural and traditional values.

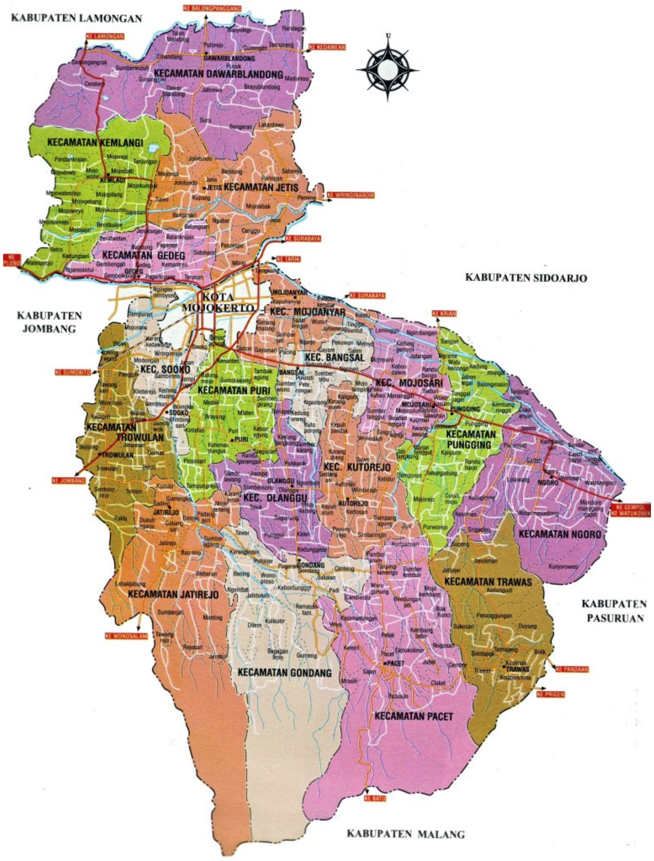

Fig 2. Mojokerto City, Indonesia

The sampling technique used is random sampling. Stratified random sampling is a type of sampling with sampling by dividing the population into strata. Through stratified random sampling, it is expected that the research can provide equal representation between public high schools in Mojokerto district and can provide relevant insights related to the acceptance of AI-based learning applications among students to support learning.

The SEM-PLS technique is employed in this study to evaluate both the outer model (measurement model) and inner model (structural model), ensuring a robust analysis of factors influencing students' Behavioral Intention and Use Behavior toward AI learning applications. This approach is chosen because it handles complex models, does not require normal data distribution, and is ideal for predictive modeling making it superior for exploratory research on AI adoption in education and after obtaining the analysis results from the previous two stages, hypothesis testing is carried out. Then to determine whether there is a direct influence between variables and the path coefficient to test the hypothesis through P-value < 0.05 or T-value > 1.96: Indicates that the path or relationship being tested is significant at the 5% level. P-value ≥ 0.05 or T-value ≤ 1.96: Indicates that the relationship is not statistically significant, and the null hypothesis cannot be rejected [34].

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III. RESULT AND DISCUSSION

3.1 RESPONDENT CHARATERISTIC

The results of data collection that have been carried out for one month in March-September 2024 have a total of 400 respondents with characteristics as in the following table.

Table 2. Respondent Demographics

Characteristics	Description	Total	%
Gender	Female	248	62%
	Male	152	38%
	Total	**400**	**100%**
Grade level	XI	211	52.8%
	XII	128	32%
	X	61	15.2%
	Total	**400**	**100%**
Frequency of Use	Once in 1 day	55	13.75%
	Several times in 1 day	134	33.50%
	Once in 1 week	25	6.25%
	Several times in 1 week	116	29%
	Once in 1 month	29	7.25%
	Several times in 1 month	41	10.25%
	Total	**400**	**100%**

Based on the respondent demographics, the acceptance of AI in schools is likely to be influenced by several factors. The majority of respondents are female (62%), and research suggests that gender can play a role in technology adoption, with some studies indicating that females may exhibit more cautious attitudes toward AI. Additionally, most respondents are in grade XI (52.8%), followed by grade XII (32%) and grade X (15.2%). Older students may have more experience with technology, which could lead to a higher acceptance rate of AI tools in education. Regarding the frequency of use, a significant portion of students (33.5%) use technology several times a day, while others use it several times a week (29%) or once daily (13.75%). This frequent exposure suggests that students are accustomed to digital tools, potentially making AI integration in learning smoother. However, a small percentage of students use technology only once a week (6.25%) or even once a month (7.25%), which may indicate a digital divide and the need for proper AI literacy programs.

Overall, the high daily engagement with technology and the dominance of senior students suggest a promising landscape for AI adoption in schools. However, factors such as gender differences in perception and the varying frequency of technology use should be considered to ensure inclusive and effective AI implementation.

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3.2 INFERENTIAL STATISTICAL ANALYSIS

The validity test was used to test the question instrument as a measuring tool in Outer Model. A valid instrument indicates that the measuring instrument used to obtain the data is also valid.

Table 3. Validity and reliability

	BI	EE	FC	HM	HT	PE	PI	PV	SI	UB	AVE	Cr
BI	**0.835**										0,698	0,893
EE	0.683	**0.758**									0,574	0,843
FC	0.669	0.747	**0.749**								0,561	0,843
HM	0.718	0.726	0.667	**0.801**							0,642	0,905
HT	0.772	0.622	0.620	0.651	**0.839**						0,703	0,856
PE	0.688	0.726	0.723	0.777	0.630	**0.766**					0,587	0,874
PI	0.615	0.643	0.669	0.680	0.528	0.657	**0.765**				0,585	0,850
PV	0.667	0.676	0.677	0.705	0.653	0.671	0.616	**0.815**			0,665	0,849
SI	0.604	0.498	0.526	0.552	0.669	0.531	0.455	0.559	**0.857**		0,735	0,836
UB	0.737	0.628	0.639	0.660	0.770	0.625	0.544	0.654	0.593	**0.848**	0,719	0,885

Based on the table 3, it is known that the variables have met the validity because each indicator has an *Average Variance Extracted* (AVE) value of more than 0.5 [35]. Discriminant validity can also be assessed using the Average Variance Extracted (AVE) root value or the Fornell-Larcker Criterion. The Fornell-Larcker Criterion is considered fulfilled when the square root of AVE for each construct is higher than its correlation with other constructs in the same model. In other words, for each column, the top value (representing the AVE root of a construct) should be the highest compared to other correlation values within that column. This indicates that the construct shares more variance with its own indicators than with any other construct in the model, thereby confirming discriminant validity.

Then, the reliability test can be interpreted as a test to determine the consistency value of a measuring device in measuring objects or variables [36]. The variables in the research questionnaire can be declared reliable if the *Cronbach Alpha* (CA) value is > 0.7 and the *Composite Reliability* (CR) value is > 0.7, and the Composite Reliability value of each variable is more than 0.7. This shows that all variables have met the reliability standards so that they can be said to be reliable. Then, testing the path coefficient to test the hypothesis through a significance test with a T value > 1.96 and a p-value below 0.05. The following are the results of hypothesis testing using SmartPLS 3.

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Table 4. Hypothesis Test Results

H.	Relation	T-value	P value	Desc
H1	PE → BI	1,065	0.268	Not Significant
H2	EE → BI	1,389	0.125	Not Significant
H3	SI → BI	1,256	0.215	Not Significant
H4	FC → BI	1,117	0.234	Not Significant
H5	**FC → UB**	**3,867**	**0.000**	**Significant**
H6	**HM → BI**	**2,326**	**0.017**	**Significant**
H7	PV → BI	0,795	0.407	Not Significant
H8	**HT → BI**	**6,697**	**0.000**	**Significant**
H9	**HT → UB**	**8,487**	**0.000**	**Significant**
H10	PI → BI	1,572	0.100	Not Significant
H11	**BI → UB**	**4,454**	**0,000**	**Significant**

Based on Table 4, of the 11 hypotheses proposed, 5 hypotheses are significant namely the relationship between BI and UB, FC and UB, HM and BI, HT and BI, and HT and UB. Performance Expectancy (PE) did not significantly affect BI, indicating that students' belief in the benefits of using the application alone is insufficient to increase their intention to adopt it. This suggests that dissatisfaction with application performance and varying learning preferences may act as barriers. This finding contrasts with prior research on AI tools like ChatGPT and similar systems, which identified insignificant relationship between PE and BI [13], *electronic document management system* [37], and AI Chatbot [38].

Similarly, Effort Expectancy (EE) exhibited a positive but insignificant effect on BI, reflecting that ease of use does not necessarily translate into higher adoption intention. Usability issues, such as complex interfaces and excessive features, were highlighted by students as barriers, consistent with findings from studies on other educational technologies. This result is in line with learning application research ChatGPT [13], AI Chatbot [38], learning management system [16], and google classroom [19].

Social Influence (SI) also had no significant impact on BI, potentially due to the lack of curriculum integration and limited promotion of AI tools within schools. This aligns with earlier research showing that social factors often have minimal influence on technology adoption in educational contexts [39]. Conversely, Facilitating Conditions (FC) positively influenced UB but not BI. While accessible resources and institutional support encourage usage, they may not directly enhance students' intention to adopt AI tools, as noted in studies on m-learning systems [40].

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Hedonic Motivation (HM) significantly influenced BI, underscoring the importance of enjoyment and satisfaction in driving technology adoption. Students perceived the engaging features of AI applications as valuable in enhancing their learning experience. However, Price Value (PV) showed no significant effect on BI, aligning with findings that monetary costs are less critical in e-learning adoption compared to social and individual factors. This result is in line with research conducted on learning applications mobile phone [41] which shows that there is no relationship between Price Value and Behavioral Intention, also revealed that price value is more influential in other service applications, such as e-commerce, e-ticketing, and e-service [42]. Habit (HB) emerged as a strong predictor, significantly affecting both BI and UB. Students with prior experience using similar applications were more likely to adopt and consistently use AI tools, supporting research on habitual technology use [43], *mobile learning* [40], and *learning management system* [44]. Researchers agree that the habit of using technology or applications can increase the intention to use the application and tend to use it actively and consistently.

In contrast, Personal Innovativeness (PI) showed no significant impact on BI, suggesting that high school students may lack awareness or readiness to adopt innovative technologies. Institutional efforts are needed to foster this characteristic among students. According to research on AI applications Chatbot [45], innovation in adopting new technology is also influenced by various factors, including the advantages of the technology. Behavioral Intention (BI) positively influenced UB, reaffirming that stronger intentions lead to higher actual usage of AI applications. This finding aligns with prior studies on AI-based learning tools, highlighting the critical role of behavioral intention in predicting technology adoption ChatGPT [20], *mediating information adoption* [46], AI Chatbot [38], and ChatGPT [13].

This result revealed that adopting AI applications in education is influenced by complex factors. The insignificant relationship between Performance Expectancy (PE) and Behavioral Intention (BI) suggests that awareness of the benefits of an app alone is not enough to increase adoption intention. Similarly, the lack of significant impact of Effort Expectancy (EE) suggests that usability issues, such as complicated interfaces and redundant features, remain significant barriers. In addition, the minimal influence of Social Influence (SI) highlights the need for institutional strategies to better integrate AI tools into the curriculum. On the other hand, Habit (HB) strongly predicted BI and Usage Behavior (UB), emphasizing the role of consistent exposure to drive adoption and sustained use.

Unlike most studies conducted at the university level, this study contributes to the literature by applying the UTAUT2 model in the context of Mojokerto Regency high school students population in AI adoption research. The findings highlight the significant roles of Habit and Hedonic Motivation in influencing both Behavioral Intention and Use Behavior, suggesting that

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enjoyable experiences and consistent usage habits are crucial for successful integration of AI in secondary education. These insights provide a localized framework for policymakers and educators aiming to implement AI tools effectively at the high school level. The following **doi:** outlines a structured framework designed to guide educators in effectively adopting and integrating AI tools into their teaching practices. Each stage is tailored to address specific objectives, ensuring a comprehensive approach to enhance the learning experience for both educators and students.

Table 5. Provide Stages to Educators Improve Use AI

Stage	Steps	Objective
Preparation	Teacher Training: Provide intensive training on using AI technologies, such as AI-based learning applications.	Equip educators with necessary skills and ensure readiness of infrastructure.
	Needs Analysis: Identify the specific needs of educators and students regarding AI-based learning.	
	Technology Provision: Ensure adequate infrastructure such as hardware and reliable internet access.	
Introduction	Application Demo: Conduct interactive workshops or demos to introduce AI applications.	Familiarize educators with AI tools and allow early exploration of their functionalities.
	Initial Testing: Engage educators in testing the application to familiarize them with its interface and features.	
Planning	Curriculum Integration: Align the use of AI applications with the existing curriculum.	Effectively integrate AI into daily lesson plans.
	Lesson Planning: Develop lesson plans that incorporate AI to support activities like discussions or practice exercises.	
Implementation	Gradual Usage: Start integration gradually, focusing on a single class or topic.	Ensure smooth implementation with active participation from all stakeholders.
	Collaboration: Encourage collaboration between students and educators using AI features such as chatbots or automated tutorials.	
Evaluation	User Feedback: Gather feedback from educators and students on their experience using the AI application.	Assess the effectiveness of AI applications in enhancing teaching and user experiences.
	Data Analysis: Use the analytics features of the AI application to evaluate students' learning progress.	

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To ensure the effective adoption of AI in education, recommendations must be grounded in empirical research and established theories rather than arbitrary suggestions. One key factor is targeted teacher training programs, which are essential for equipping educators with the skills needed to integrate AI into their teaching practices. Studies have shown that teachers' confidence and preparedness directly influence technology adoption in classrooms [47]. Without proper training, AI tools may be underutilized or misapplied, limiting their potential benefits. Furthermore, adaptive AI-driven learning systems have been proven to enhance student engagement and learning outcomes [48]. Developers should focus on creating personalized, gamified, and accessible learning environments to accommodate different cognitive abilities and learning styles [49].

Beyond training and accessibility, the collaboration between educators and AI developers is crucial for ensuring that AI applications meet practical classroom needs rather than being technologically sophisticated but pedagogically ineffective [50]. Educators understand the real challenges of teaching, while developers bring technical expertise, making co-design essential for creating AI tools that truly enhance learning [10]. Research further supports that AI adoption is most successful when teachers are involved in the development process, ensuring usability and alignment with learning objectives [6]. Thus, AI adoption in education must be approached systematically grounded in research, supported by training and accessibility measures, and driven by collaborative innovation to maximize its impact on student learning and educational transformation.

To increase AI adoption in education, targeted teacher training programs are essential. Educators must be equipped to understand and effectively apply AI in their teaching practices, from selecting appropriate tools to tailoring them to the needs of diverse students. Developers, in turn, should focus on creating adaptive features that respond to individual learning styles, integrate gamification to increase engagement, and ensure accessibility for students with different abilities. Collaboration between educators and developers is essential to design tools that meet practical needs in the classroom.

IV. CONCLUSION

The study concludes that the acceptance and usage behavior of AI-based learning applications in education especialy high school students are influenced by key factors, including facilitating conditions, hedonic motivation, habit, and behavioral intention. Despite general acceptance, suboptimal usage behavior persists, driven by user experience, app response speed, and the lack of integration into school curricula. This study makes a significant contribution by extending the UTAUT2 model to high school education, providing actionable insights for developers to enhance

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app usability and for educators and policymakers to integrate these technologies effectively into teaching systems. These findings underscore the potential for AI applications to transform education, while also highlighting areas for improvement to optimize their adoption and use.

However, this study is limited to a cross-sectional survey within public high schools in Mojokerto Regency, which may not fully capture the dynamics of AI usage in other educational contexts. Future studies are recommended to explore AI adoption in diverse educational settings such as private schools or vocational institutions. Additionally, incorporating qualitative methods could provide deeper insights into students' perceptions and experiences. Further research involving other stakeholders, such as teachers or parents, may also enhance understanding of the broader ecosystem influencing AI integration in education.

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