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THE INFLUENCE OF PREDICTOR FACTORS ON BEHAVIORAL INTENTION TO IMPLEMENT AI-PROCTORED ONLINE ASSESSMENT

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Abstract:

The purpose of this study was to identify the factors influencing educators' behavioural intention to implement AI-proctored online assessments (automated proctoring) and to determine the strength of these predictor factors. The focus of this study is on health science programmes involving formative and summative assessment. This study was necessary to the institution make plans related to the use of AI in assessment. A total of 260 educators from 14 Institut Latihan Kementerian Kesihatan Malaysia (ILKKM) were selected using simple random sampling. The study employed a questionnaire adapted from the Unified Theory of Acceptance and Use of Technology (UTAUT). Data were analysed using SPSS version 27 through descriptive and inferential statistics, including mean, standard deviation, and multiple regression analysis. The results indicated that performance expectancy ($M = 4.14$, $SD = .806$), effort expectancy ($M = 4.23$, $SD = .746$), social influence ($M = 3.95$, $SD = .794$), and behavioural intention ($M = 4.06$, $SD = .807$) were at high levels, while facilitating conditions ($M = 3.60$, $SD = .909$) were at a moderate level. Multiple regression analysis revealed that effort expectancy, social influence, and facilitating conditions significantly influenced behavioural intention. Social influence emerged as the strongest predictor ($\beta = .778$, $p < 0.05$), contributing 60.5% of the variance change ($R^2 = .605$). The combination of social influence and effort expectancy increased the explained variance to 67.0% ($R^2 = .67$), while the inclusion of facilitating conditions raised it to 71.5% ($R^2 = .715$). In conclusion, social influence, effort expectancy, and facilitating conditions play significant roles in shaping educators' behavioural intention to implement AI-proctored online assessments within the ILKKM context. By

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identifying the predictor factors influencing this intention, the effectiveness of implementing AI-proctored online assessments at ILKKM can be enhanced.

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Keyword:

AI-Proctoring, Effort Expectancy, Facilitating Condition, Online Assessment, Social Influence

Introduction

Online assessments are known as technology-based assessments. It refers to an efficient method to assess students' performance or learning within an online setting. In other terms, online assessments serve as a means to measure students' academic performance, achievement, and progress throughout the educational process (Iskandar et al., 2021). In this study, online assessment refers to examinations or tests conducted electronically through the internet. These examinations also involve the use of technology to deliver, manage, and implement assessments related to online assessment. Meanwhile, artificial intelligence (AI) is a concept that has existed since the 1950s, which was created by a mathematician, Alan Turing. AI is a set of computer programs and technologies designed to stimulate intelligence and cognitive function (Huang et al., 2019). This is because AI-proctored exams can monitor candidates simultaneously without requiring a large number of human resources. Therefore, it can reduce costs. In addition, the proctor is also consistent and unbiased. Nowadays, AI technology has increasingly advanced in the field of education, one of which is the use of proctoring systems or digital monitoring systems during online examinations. According to Udechukwu (2020), digital monitoring systems involve the use of digital tools and technologies to ensure that students comply with guidelines and policies when taking examinations online. Since online assessment has become the preferred approach for most educational institutions, virtual monitoring during examinations is essential to maintain students' integrity while the examination is in progress. Digital monitoring also facilitates the administration of remote examinations without the need for in-person supervision (Gonzales et al., 2020).

Background of Study

The advancement of digital technology has brought significant changes to teaching delivery and assessment methods in higher education. Since the COVID-19 pandemic, online learning

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and online assessment have been widely implemented, compelling educators to adapt to these platforms. Following the COVID-19 pandemic, the global expansion of online learning and assessment has forced education practitioners to adapt to entirely new online platforms. Institut Latihan Kementerian Kesihatan Malaysia (ILKKM), a health training institute under the Ministry of Health Malaysia that offers health science-related certificate, diploma, professional certificate, and advanced diploma programs, also has been involved in the transition.

In any assessment system, the integrity and credibility are core to assuring the quality. The integrity must be maintained throughout the assessment process starting from item development, execution, grading until the issuance of academic transcripts. The important component for students is during assessment. They must be strictly compliance with relevant regulations. Academic integrity violations including plagiarism, cheating, and misappropriation of others' work are strictly prohibited. In ensuring to maintain academic integrity during online assessment, AI based proctoring is one of the main approaches. However, educators' acceptance regarding of the use of this technology plays an important role in the effectiveness of its implementation (Xu et al., 2024). Therefore, this study aims to explore the level of educator's acceptance towards online assessment based on AI proctoring and identify factors the influence their acceptance.

Problem Statement

Online assessment based on AI proctoring seen as capable of improving academic integrity by direct monitoring and identifying suspicious behavior during online examination. These systems offer automated monitoring and help reduce academic cheating tendencies. However, the effectiveness using this technology depends on educators' acceptance to adopt and implement it in education setting. According to Coghlan et al. (2020) the implementation of AI proctoring has brought out mixed reactions among educators, especially in relation to issues of trust, ethics, privacy, and feasibility. Some educators question to the accuracy of AI in identifying academic misconduct and concern about its potential negative impact on teaching relationships and student trust. At ILKKM itself, some tutors remain hesitant to use AI-proctored assessments due to concerns about technical reliability, data privacy, and fairness. If this hesitation persists, the full benefits may not be achieved. Most research on technology acceptance in education has mainly focused on Learning Management Systems (LMS) and e learning. However, study on acceptance of AI proctoring systems during online assessments are limited. As a result, the specific factors influencing educators' intentions to implement AI-proctored assessments remain underexplored. Addressing this gap, this study aims to explore the influence of predictor factors on educators' behavioural intention to implement AI-proctored online assessment at ILKKM. This study was guided by the Unified Theory of Acceptance and Use of Technology (UTAUT). These findings can support institutional strategies for the use of AI-proctored online assessment in health science education.

Research Objectives

Based on the research problem statement, the researcher has established two research objectives as follows:

i. To identify the mean scores of performance expectancy, effort expectancy, facilitating conditions, social influence, and behavioural intention towards the implementation of AI- proctored online assessments among educators in ILKKM across Malaysia.
ii. To determine the influence of performance expectancy, effort expectancy, facilitating

International Journal of Modern Education
IJMOE
EISSN: 2637-0905
Volume: 8 Issue: 30 (June 2026) PP. 577-589

conditions, and social influence on behavioural intention in the implementation of AI-proctored online assessment among educators in ILKKM across Malaysia.

Research Questions

Based on the research objectives, the following research questions were formulated:

i. What are the mean scores of performance expectancy, effort expectancy, facilitating conditions, social influence, and behavioural intention towards the implementation of AI- proctored online assessments among educators in ILKKM across Malaysia?
ii. What is the influence of performance expectancy, effort expectancy, facilitating conditions, and social influence on behavioural intention in the implementation of AI-proctored online assessment among educators in ILKKM across Malaysia?

Research Hypothesis

$H_{o:}$ There is no significant influence of performance expectancy, effort expectancy, facilitating conditions, and social influence on behavioural intention towards the implementation of AI-proctored online assessment among educators in ILKKM across Malaysia.

Literature Review

AI-proctored online assessments allow monitoring through a computer system and webcam. Various software applications now offer an AI-driven proctoring system which is it can be integrated with a learning management system. So that examination activities can be recorded for the purpose of observing students during online assessment. With that, the issue of academic dishonesty can be reduced through the implementation of AI-proctored assessment (Jia & He, 2022). For example, in ILKKM itself, the report of academic integrity during the implementation of online assessment is one of the required documents by Malaysian Qualification Agency (MQA). Study conducted by Alice (2022) reported that 72% of students was not easy to cheat in online examinations when AI proctoring was applied. This view was supported by the study conducted by Dendir and Maxwell (2020), which found that there was a significant difference in examination scores between unproctored and proctored assessments. This suggests that online proctoring is an effective approach in reducing cheating during online examinations. While Herliana et al. (2022) argued that the autoproctor feature in Google Form, which is based on three elements- sound recordings, video camera input, and screen activity on students' devices was not able to provide accurate analysis. Sound recordings may be influenced by environmental noise, while facial recordings may be incomplete depending on the positioning of the device during the examination. However, the limitation of their study is only to the software available in Google Forms. It is possible that other software might perform more effectively. Therefore, AI-proctored systems can be a useful guide for educators to implement this application as a way to foster honesty among students and enhance the quality of online assessment as well as adapt to new norms in line with technological developments.

A study conducted in a private university in Northern Cyprus found that many educators were receptive to AI-proctored systems such as Safe Exam Browser (SEB) as a means of increasing transparency in assessment processes, thereby addressing issues of impersonation and academic dishonesty (Ironsi, 2021). However, they also expressed concerns that students may not be able to take examinations in a calm environment, as their personal data could be accessed

International Journal of Modern Education
IJMOE
EISSN: 2637-0905
Volume: 8 Issue: 30 (June 2026) PP. 577-589

by the companies managing the AI-proctoring systems. Similarly, Conijn et al. (2022) emphasised that continuous monitoring during online assessments has the potential to infringe on students' privacy rights and cause discomfort. Sridhar and Rajshekhar (2022) also agreed that AI monitoring systems are closely associated with challenges such as unstable internet connectivity, personal data exposure, privacy issues and high software costs which may not be reasonable for some institutions.

To further explain regarding this study on educators' acceptance of AI-proctored online assessment, the UTAUT model is employed as the theoretical framework. Venkatesh et al., (2003) was introduce the UTAUT as a comprehensive model which is integrating eight previous models related to technology acceptance, including the Technology Acceptance Model, Theory of Reasoned Action, Innovation Diffusion Theory, Theory of Planned Behaviour and the Model of Personal Computer Utilisation. This model has been widely used to explain and predict individual intention and behaviour in adopting technology. For example, Thangarajan and Mohd Rusli (2024) applied the UTAUT model to explain teachers' acceptance of information and communication technologies in education. Beyond an education, the model has also been applied in various fields such as healthcare, industry, and AI-based proctoring in assessment. For instance, Permassari and Salamah (2024) used the model in the industrial sector to examine factors influencing user acceptance of digital websites and their impact on user satisfaction. Thus, the UTAUT model is versatile and relevant in examining technology adoption.

Figure 1 refers to UTAUT model which consists of 4 main components that influence behavioral intention to use technology. The 4 components are performance expectancy (PE), effort expectancy (EE), social influence (SI) and facilitating conditions (FC).

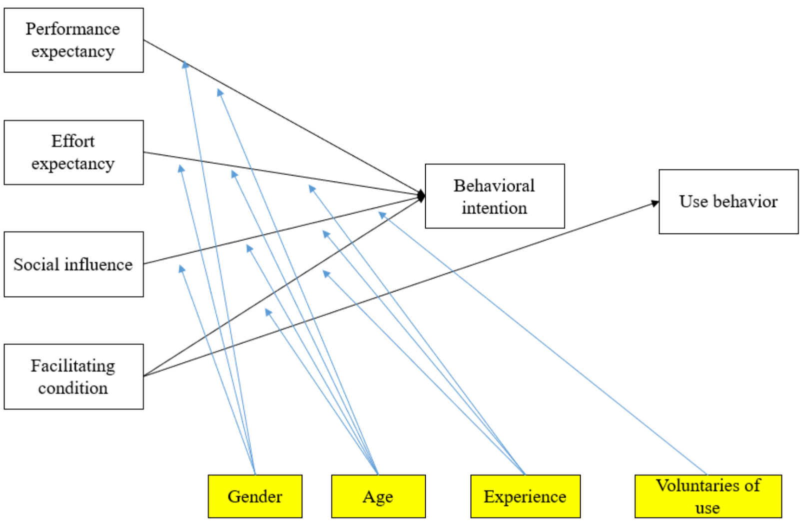

Figure 1: Unified Theory of Acceptance and Use of Technology (UTAUT)
Source: (Venkatesh et al., 2003)

PE refers to the degree of an individual who believes that using technology will improve job performance. Abdul Rahim et al. (2021) found that technology is more accepted in education when it is perceived to provide benefits for both teachers and students. In this study, PE refers to how much an educator believes that AI-proctored online assessments can enhance effectiveness and uphold academic integrity.

While EE refers to the useability of a system and technology. If educators perceive AI-based proctoring systems as user friendly and not burden, then they are more tendency to accept them. SI refers to how much an individual's decision to use technology is influenced by others, such as colleagues or administrators. In this study, SI refers to how peer educators' and institutional leaders' support may shape educators' acceptance of AI-proctored online assessments. According to Thohir et al. (2023), Facilitating Conditions (FC) are a crucial factor influencing educators' acceptance of educational technologies. Adequate infrastructure and technical support such as training, IT assistance, computer labs, internet access and wireless fidelity (Wi-Fi) is essential to ensure effective acceptance (Amora & Fearnley, 2020). Therefore, institution must provide sufficient resources and support to implement AI-based online examinations effectively.

In addition to the four main components, the Unified Theory of Acceptance and Use of Technology model also considers moderator variables such as gender, age, experience and voluntariness of use which may influence the strength of relationships between the components and behavioural intention. Overall, the UTAUT model provides a robust theoretical framework for understanding the factors influencing technology adoption among users. Its applicability to various contexts makes it highly relevant to this study which investigates educators' acceptance of AI-proctored online assessments.

Methodology

This study employed a survey design utilising an online questionnaire with a quantitative approach. The data were analyzed using descriptive and inferential statistics. The data were collected from 14 ILKKM across Malaysia which offer certificate, diploma, post-basic, and advanced diploma programs in the allied health sciences. The study sample comprised 260 educators selected through simple random sampling. This questionnaire was divided into two parts. Section A, contained sociodemographic data, including age, gender, ethnicity, educational level and teaching experience, while Section B measured educators' acceptance.

This section was adapted from the instruments developed by Al-Anezi & Alajmi (2021) and Ayaz & Yanartas (2020), based on the UTAUT model by Venkatesh et al. (2003). The questionnaire contained 20 items designed to assess educators' acceptance in implementing AI-proctored online assessments. A five-point Likert scale was employed, ranging from strongly disagree to strongly agree. Data analysis was performed using SPSS 27.0, employing descriptive statistics included mean distribution and standard deviation, while inferential statistic employed multiple regression analysis to identify predictor factors.

Results and Discussion

Mean Score Analysis

Table 1 presents the overall mean scores for the predictor variables of behavioural intention to implement AI-proctored online. Effort expectancy achieved the highest average score at 4.23 (SD = .75), followed by performance expectancy with a mean of 4.14 (SD = .81), intention with a mean of 4.06 (SD = .81), and social influence with a mean of 3.95 (SD = .79). To discuss the acceptance of this technology, the interpretation of the mean scores is based on Nunnally & Bernstein (1994). This interpretation is chosen for its detailed explanation, a scale ranging

International Journal of Modern Education
IJMOE
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Volume: 8 Issue: 30 (June 2026) PP. 577-589
from 1.00 to 5.00. Specifically, a mean score between 1.00 and 2.33 reflects a low level of acceptance, scores from 2.34 to 3.66 indicate a moderate level, and scores between 3.67 and 5.00 represent a high level of acceptance. According to finding, all four factors were at a high level. Meanwhile, the analysis of facilitating conditions indicated a moderate level, with a mean score of 3.60 (sd = .91). These results align with previous studies that have reported facilitating conditions were at a moderate level (Zhou et al., 2022; Mohd Noor & Wan Ismail, 2024). This situation may suggest that the institutions face certain limitations with regard to facilitating conditions.

Table 1: Mean Score of Predictor Factors

Variable	Mean±std dev (n=260)	Interpretation
Performance Expectancy	4.14±0.81	High
Effort Expectancy	4.23±0.75	High
Social Influence	3.95±0.79	High
Facilitating Conditions)	3.60±0.91	Moderate
Intention	4.06±0.81	High

Analysis of the Influence of Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions on Behavioural Intention to Implement AI-proctored Online Assessment

A stepwise multiple regression analysis was performed to identify the significant predictors of the dependent variable. The findings indicate that social influence significantly affected the educator's intention to implement AI-proctored online assessments (p value $< .05$). Consequently, the null hypothesis was rejected. This result is aligned with previous studies by Iqbal & Tahir (2023) and Permassari & Salamah (2024). Educators perceived that AI-proctored online assessments were influenced by important individuals such as fellow educators. Consequently, educators were more likely to accept online assessment when they received full support from higher authorities. This view is aligned with Kee Mohd Yussof et al. (2021), who argued that the use of technology requires a support system from peers and administrators within an educational organization. Effort expectancy was also found to significantly influence the educator's intention to implement AI-proctored online assessments.

Hence, the null hypothesis was rejected. This finding is consistent with studies by Iqbal & Tahir (2023) and Rahmawati (2023), but contrasts with the results of Permassari & Salamah (2024), which reported that effort expectancy did not significantly influence technology adoption. These findings suggest that educators tend to accept AI-proctored online assessments if the technology is easy to use and does not impose additional burdens on them.

The third predictor is facilitating conditions also demonstrated a significant impact on the educator's intention to implement online assessments using AI proctoring systems (p value $<$ .05). Thus, reject the null hypothesis. This result is aligned with the findings of Kee Mohd Yussof et al. (2021), Iqbal & Tahir (2023), and Rahmawati (2023). The results suggest that sufficient technical support and infrastructures are essential for the successful implementation

International Journal of Modern Education
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IJMOE
Volume: 8 Issue: 30 (June 2026) PP. 577-589

of AI-proctored online assessments including training, IT support, and access to technological resources. Similarly, Mohamed Nazul (2020) emphasized that the availability of infrastructure, strong support networks, and comprehensive documentation are necessary from the planning stage through implementation and monitoring of online assessment. This may also represent one of the main challenges for educators in implementing AI-proctored online assessments. In contrast, performance expectancy did not have a significant impact on the educator's intention to implement AI-proctored online assessments. Therefore, the null hypothesis was accepted. This finding is consistent with the study by Kee Mohd Yussof et al. (2021).

In conclusion, three predictor factors effort expectancy, social influence, and facilitating conditions significantly influenced the intention to implement AI-proctored online assessments and these three factors can be incorporated into the regression model.

Summary of Regression Model

Table 2 presents a summary of the regression model involving the predictor variables and the dependent variable. The regression analysis results indicated that Model 1 with an R^2 value of .605 demonstrated that 60.5% of the variance in the dependent variable through social influence, with an r value of .778 indicating a strong level of regression. Model 2 reported an r value of .819 also indicating a strong level of regression. The R^2 value of .670 demonstrated the combined contribution of social influence and effort expectancy to the behavioural intention of implementing AI-proctored online assessments explaining 67.0% of the variance.

Meanwhile, the combination of three predictor variables, effort expectancy, social influence and facilitating conditions accounted for 71.5% (r = .846) of the variance in the behavioral intention. All three models demonstrated strong regression outcomes, consistent with the guidelines proposed by Sheridan and Lyndall (2003).

Overall, three regression models demonstrated that social influence was a strong predictor factor of the intention to implement AI proctored online assessment. In practice, this means that when the top management of an institution supports the use of AI proctored in online assessment, educators tend to be more open to using this system. This result aligns with previous studies conducted by Daniali (2022), Iqbal and Tahin (2023), and Bempah (2025).

In the third model indicate that three predictor factors that shaped this intention. These include institutional support, adequate facilities such as LMS and stable internet access and training and technical support. In context of ILKKM, the third model appears to be suitable for predicting educators' intention to use online assessment. However, there may still have mediating factors that could influence the intention to implement online assessment practices.

Table 2: Summary of Regression Model

Model (variable)	R	R^2	Adjusted R square	SE
1 (social influence)	.778	.605	.603	2.034
2 (social influence, effort expectancy)	.819	.670	.668	1.861

3 (social influence, effort expectancy, facilitating conditions)	.846	.715	.712	1.734

Variants Analysis (ANOVA)

The effort expectancy, social influence and facilitating conditions significantly influence the behavioural intention to implement AI-proctored online assessments (refer to table 3 in the Appendix). F value shows a significant linear relationship between social influence and behavioural intention ($F(1, 258) = 394.646$, $p < .05$). The combination of social influence and effort expectancy also significantly affect the behavioural intention, ($F(2, 257) = 261.420$, $p < .05$). Furthermore, the combination of social influence, effort expectancy, and facilitating conditions had a significant influence on behavioural intention at a significant level, with $F(3, 256) = 214.051$, $p < .05$. Therefore, the null hypothesis (Ho), which states that effort expectancy, social influence and facilitating conditions do not have a significant influence on the behavioural intention to implement AI-proctored online assessments is rejected.

Regression Analysis of Effort Expectancy, Social influence and Facilitating Conditions on Behavioral Intention

Table 4 shows the strength of the relationships between the variables. The analysis results point out that for the study population (N = 260), three predictor variables were identified as predictors of the behavioural intention to implement AI-proctored online assessment. All three predictor factors showed $p < .05$, indicating a significant influence. Social Influence emerged as the primary factor influencing behavioural intention among educators ($\beta = .778$, $p < .05$), contributing 60.5% of the variance ($R^2 = .605$). The combination of social influence ($\beta = .466$, $p < .05$) and effort expectancy ($\beta = .404$, $p < .05$) increased the explained variance by 6.5% (67.0 – 60.5) ($R^2 = .67$). Meanwhile, the combination of three factors, social influence ($\beta = .259$, $p < .05$), effort expectancy ($\beta = .376$, $p < .05$), and facilitating condition ($\beta = .311$, $p < .05$) contributed 71.5% of the variance in behavioural intention among educators ($R^2 = .715$).

Table 4: Regression Analysis of Effort Expectancy, Social influence and Facilitating Conditions on Behavioral Intention

Model	Variable	B	β	Nilai t	P	R^2	Contribution
1	Social influence	.791	.778	19.866	.00	.605	60.5%
2	Social influence	.473	.466	.825	.00	.670	67.0%
	effort expectancy	.437	.404	7.161	.00		
3	Social influence	.264	.259	4.194	.00	.715	71.5%
	effort expectancy	.407	.376	7.122	.00		
	facilitating conditions	.277	.311	6.324	.00		

Conclusion

In conclusion, educators at ILKKM demonstrate an intention to implement AI-proctored online assessment if the method is easy to use and does not impose additional burdens on them. In addition, support from colleagues and top management plays a crucial role, while the provision of adequate facilities by the institution is essential to ensure the effective implementation of

AI-proctored online assessments. Therefore, technological elements should be given priority and attention by institutions in line with the ongoing transformation of national education. Emphasis should not only be placed on knowledge and skills but must also align with the demands of Education 4.0. The transformation of the national education system requires educators and tutors to equip themselves with various technological competencies. Moreover, this study enhances the understanding of the factors influencing the educator's intention to implement AI-proctored online assessments. The findings support the validity of the UTAUT model and indicate that the model is suitable for predicting educators' behavioural intention to adopt AI-proctored online assessment. It is hoped that these results will provide practical implications for higher education institutions especially Institut Latihan Kementerian Kesihatan Malaysia. Hence that, more strategic and effective approaches will be formulated to realize the implementation of AI proctored in online assessment practices with an ethical and efficient manner. This study also can provide an effective contribution to the literature of AI technology acceptance in educational context. Therefore, future studies can be conducted using advanced analyses such as Structural Equation Modelling to examine and explain the complex relationships among variables. Furthermore, new online assessment policies should be formulated to improve educator readiness in using AI during assessment.

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Author Contribution Statement:	All authors contributed significantly to the development of this manuscript. Suriyani Mohri was responsible for the literature review, conceptualization, methodology, handled data collection, analysis, interpretation of results and critical revision of the manuscript. Hishamuddin Ahmad acted as supervisor by organizing the entire study. All authors read and approved the final version of the manuscript prior to submission.

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Volume: 8 Issue: 30 (June 2026) PP. 577-589

Appendix

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1633.406	1	1633.406	394.646	.000[b]
	Residual	1067.840	258	4.139		
	Total	2701.246	259			
2	Regression	1811.037	2	905.519	261.420	.000[c]
	Residual	890.209	257	3.464		
	Total	2701.246	259			
3	Regression	1931.311	3	643.770	214.051	.000[d]
	Residual	769.935	256	3.008		
	Total	2701.246	259			

a. Dependent Variable: Intention

b. Predictors: (Constant), Social influence

c. Predictors: (Constant), Social influence, effort expectancy

d. Predictors: (Constant), Social influence, effort expectancy, facilitating conditions