

Measuring Student Adoption of Digital Platforms for Distance Education among University Students in Malaysia

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Received: 23 September 2023 | Accepted: 27 November 2023 | Published: 1 December 2023

DOI: <https://doi.org/10.55057/ijares.2023.5.4.2>

Abstract: *A discipline of education known as distance education or distance learning focuses on the pedagogy, technology, and instructional system design that successfully delivers education to students who are not physically "on-site" to get their education. Instead, they can exchange written or electronic materials asynchronously (at times of their choice) or synchronously (in real-time) using technology. A hybrid or blended course or program combines online learning with on-site attendance for any reason, including completing exams. Since then, colleges have used remote learning in conjunction with modern information technology to expand their market outside their immediate surroundings. Therefore, this study was performed to measure student adoption of digital platforms for distance education among university students in Malaysia. This study uses primary data collection with self-administered questionnaire development. The sample size is 100 students which represents the population of students that registered for distance education programs. The underpinning theory for this study is the Information System Success Model (ISSM). There are three independent variables: information quality, system quality, and service quality. According to the findings, information quality, system quality, and service quality, all have a positive and substantial impact on the intention to adopt digital platforms for distance education. This work will benefit academics, decision-makers, and system designers by providing useful implications for generating appropriate methods and building successful and practical ways to develop the online learning system of distance education.*

Keywords: Distance learning, Information System Success Model, University Students, Malaysia

1. Introduction

Education is important in the development of human skills and it is the most efficient catalyst for social change. Educational institutions are the most important institutions that can deliver knowledge and contribute to the development of knowledge. Far beyond the realms of elementary and secondary school, higher education encompasses specialized and advanced learning, nurturing intellect, critical thinking, and personal growth. Higher education institutions serve as a gateway to knowledge, expertise, and innovation, empowering students to become specialists in their chosen areas. Thus, higher education institution is looking for a

unique capacity to develop skills and foster knowledge, and the potential to mobilize educational resources and provide learning opportunities.

In Malaysia, distance education is offered for students who already work and would like to further study at the same time. So, employees are registered as part-time students also known as distance education. The advantage of distance education is employees can further study without resigning from work. The classes are conducted during the weekend. Thus, many higher education institutions in Malaysia were offered distance education to encourage more people to further study at the top level. According to Tahir (2001), universities need to create more opportunities, particularly for the training of staff at higher education institutions because the lecturers will teach the experienced students.

Currently, the development of technology gives an advantage in the process of teaching and learning. One of the most important advantages is the class can be delivered using an online platform without any need for students to come to the classroom. Lecturers and students just stay at home and they can communicate using online platforms such as Webex meetings, Google Meet, Zoom platform, and others platform. Even though this platform gives an advantage to the lecturers and students, however, the adaption of students to using the online platform is still lacking. This is because internet access is low, not enough facilities, and lack of knowledge to use online platforms. Thus, this study tries to investigate the adoption of students to use online platforms for distance education. This study used the Information Systems Success Model (ISSM) to measure the adoption of students using online platforms.

2. Literature review

The Information Systems Success Model (ISSM) is an information systems theory that seeks to provide a comprehensive understanding of information systems success by identifying, describing, and explaining the relationships among six of the most critical dimensions of success along which information systems are commonly evaluated. ISSM model was developed in 1992 to measure organizational information system success. It comprises six constructs including information quality (IQ), system quality (SQ), user satisfaction (US), individual impact (II), organizational impact (OI), and use (U) (Iqbal, et al., 2022). Numerous research is currently using the ISSM model to examine how well individuals understand information systems (Legramante, et al., 2023).

The current study also expands the applications of the information system success model and technology acceptance model. The study from Won et al., (2023) shows that app users who viewed branded sports apps as having a higher level of system and information quality were likely to have stronger perceptions of enjoyment, usefulness, and ease of use. Chen, et al., (2016) reveal that attitude toward using information systems is significantly and positively affected by perceived usefulness, perceived ease of use, and user satisfaction. Sayaf (2023) validated the theoretical concepts and the information system success model on e-learning platforms for user satisfaction indicating that all the variables are supported. Devisakti and Muftahu (2023), showed that performance expectancy and facilitating conditions have a significant relationship with digital usage. In addition, personal innovativeness has a positive significant effect on performance expectancy and effort expectancy. Thus, various studies supported the ISSM model as a suitable model for measuring the usage of information systems.

The development of the education system also introduced many modes of study. One of the most famous modes of study is distance education. According to Schlosser and Simonson

(2002), there are four main components of distance education. First, to differentiate distance education from self-study, distance education must be institutionally based. Second, there must be a separation of teacher and learner in terms of geography, time, and knowledge of the concepts to be taught. Thirdly, some form of interactive telecommunications must be available for learners to interact with each other, with the resources of instruction, and with the teacher (Rice, 2006). One of the most important indicators in revealing the effectiveness of the distance education process is the satisfaction level of the learners. The study by Unal et al., (2023) suggested that learners' satisfaction is one of the most important factors in determining the effectiveness of distance education. While study from Kilinc (2023) emphasizes the need to harness technology, cultivate a sense of community, and encourage educators to pursue continual professional development to improve the quality and participation of distance scientific education. Thus, most studies suggested that distance education can contribute to valuable insights (Baser, 2022; Giacomazzi et al., 2022).

The study by Altinay, et al., (2019) regarding distance education suggests that distance education contributes to providing equal opportunities in education. It is of great importance that individuals are aware of their roles in the process of accessibility, institutional support, technological infrastructure, support provided for students, learning-teaching environments, and evaluation of distance education programs based on equality and life-long learning. Thus, the main objective of this study is to measure student adoption of digital platforms for distance education among university students in Malaysia.

3. Research methodology

This study uses a questionnaire to measure student perception towards the adoption of digital platforms for distance learning. Every construct has 5 questions as measurement items. The underpinning theory is the Information System Success Model (ISSM). This study uses multiple linear regression as a method to evaluate the influence of independent variables on dependent variables.

The population for this study is university students who enrolled in education learning programs in Malaysia. This study implemented simple random sampling to select the respondents. Next, the analysis was performed using Multiple Linear Regression for hypothesis testing.

The research framework is shown in Figure 1. There are three independent variables: Information Quality, System Quality, and Service Quality. Information System Success Model (ISSM) is a model developed by DeLone and McLean in 1992. DeLone and McLean (1992) explain a comprehensive review of different information system success measures that concludes with a model of "temporal and causal" interdependencies between their six categories of Information System Success. This theory is selected for this study because of its relevance to the objective of measuring student adoption of digital platforms that are considered as one of the information systems.

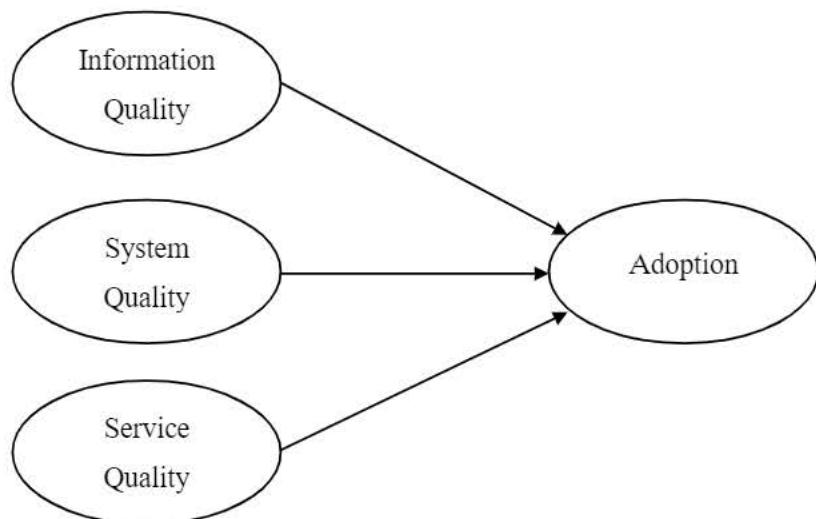


Figure 1: Research framework

This study has three hypotheses that need to be evaluated.

H1: There is a positive and significant influence of Information Quality (InfoQ) towards the Adoption (A) of digital platforms for distance learning among university students in Malaysia.

H2: There is a positive and significant influence of System Quality (SysQ) towards the Adoption (A) of digital platforms for distance learning among university students in Malaysia.

H3: There is a positive and significant influence of Service Quality (SerQ) towards the Adoption (A) of digital platforms for distance learning among university students in Malaysia.

4. Result and discussion

This study analyzed the descriptive statistics and multivariate linear regression analysis to assess the research hypothesis. The number of independent variables is Information Quality (IQ), System Quality (SQ), and Service Quality. The independent variable is student adoption of digital platforms for distance education.

4.1 Descriptive statistics

Descriptive statistics summarize the characteristics of a data set. There are three types: distribution, central tendency, and variability. Table 1 shows the descriptive statistics for 4 variables involved in this study. The sample size is 100 respondents. To demonstrate a normal univariate distribution, skewness, and kurtosis values between -2 and +2 are considered acceptable (George & Mallery, 2010; Hair et al., 2010; Bryne, 2010; Kline, 2011). Table 1 shows the value of skewness and kurtosis for Information Quality, System Quality, Service Quality, and Adoption are between -1 and +1. Therefore, all four variables are normally distributed data.

Table 1: Descriptive statistics for the sample

Variable	N	Mean	S.D.	Skewness	Kurtosis	Normality
IV1: Information Quality	100	3.4617	.74298	-.048	-.550	Yes
IV2: System Quality	100	3.4006	.74544	.011	-.103	Yes
IV3: Service Quality	100	3.3370	.63639	.007	-.582	Yes
DV: Adoption	100	3.5070	.69833	-.005	-.530	Yes

4.2 Statistical normality test

This study uses the Shapiro-Wilk test to evaluate the normality of data distribution. The Shapiro-Wilk test is a statistical test that determines if a set of data follows a normal distribution. The Shapiro-Wilk test is a goodness-of-fit test in essence. In other words, it looks at how well the sample data fits a normal distribution (Shapiro and Wilk, 1965; Royston, 1982a; Royston, 1982b; Royston, 1995). For the Shapiro-Wilk test, the null hypothesis is that the sample comes from a normal distribution, and the alternative hypothesis is that it does not. In the Shapiro-Wilk W test, the null hypothesis is that the sample is taken from a normal distribution. This hypothesis is rejected if the critical value P for the test statistic W is less than 0.05. Table 2 shows all four variables follow normal data distribution.

Table 2: Shapiro-Wilk normality test

Variable	Statistic	df (degree of freedom)	Significant (p-value)	Normality (p-value > 0.05)
IV1: Information Quality	.987	100	.417	Yes
IV2: System Quality	.985	100	.342	Yes
IV3: Service Quality	.987	100	.468	Yes
DV: Adoption	.988	100	.537	Yes

4.3 Statistical normality test

One of the assumptions of regression, the independent variable and dependent variable should have a linear relationship. This can be measured using the Pearson correlation coefficient. The Pearson correlation coefficient (r) is the most often used method of calculating a linear correlation. A number between -1 and 1 represents the intensity and direction of the link between two variables. A -1 means there is a strong negative correlation and +1 means that there is a strong positive correlation. A 0 means that there is no correlation. The absolute value of the correlation coefficient indicates the relationship strength. The larger the number, the stronger the relationship (Mukaka, 2012; Altman and Bland, 1983; Selvanathan, 2020). Table 3 shows all independent variables have a high-linear relationship with the dependent variable. This meets with the assumption for regression analysis.

Table 3: Linear relationship analysis

Relationship	Pearson correlation coefficient	p-value	Interpretation
IV1 > DV	0.623	0.000	High linear relationship
IV2 > DV	0.602	0.000	High linear relationship
IV3 > DV	0.632	0.000	High linear relationship

4.4 Multicollinearity test

Multicollinearity is the occurrence of high intercorrelations among two or more independent variables in a multiple regression model. It usually happens when the independent variables in a regression model are highly correlated with each other. This association is unexpected since the independent variables are thought to be independent. If the degree of this association is high, it may present complications for anticipating model outcomes (Kim, 2019). Coefficients become very sensitive to small changes in the model. It reduces the statistical power of the regression model.

Strong multicollinearity increases the variance of a regression coefficient. The increase in the variance also increases the standard error of the regression coefficient (because the standard error is the square root of the variance). The increase in the standard error leads to a wide 95% confidence interval of the regression coefficient. The inflated variance also results in a

reduction in the t-statistic to determine whether the regression coefficient is 0. With a low t-statistic value, the regression coefficient becomes insignificant. The wide confidence interval and insignificant regression coefficient make the final predictive regression model unreliable (Liao and Valliant, 2012).

If the correlation coefficient is > 0.85 , then it is suspected that multicollinearity occurred in the model. Conversely, if the correlation coefficient is ≤ 0.85 , it is assumed that the model did not contain multicollinearity (Gujarati, 2004). Table 4 shows the values of the Pearson correlation coefficient between independent variables are less than 0.4. Therefore, all the independent variables do not exhibit serious multicollinearity.

Table 4: Linear relationship analysis

Relationship	Pearson correlation coefficient (r)	Serious multicollinearity (r>0.85)
IV1 ↔ IV2	0.260	No
IV1 ↔ IV3	0.366	No
IV2 ↔ IV3	0.357	No

4.5 Regression analysis

Next, this study proceeded to the regression analysis because all the variables meet the assumption of multivariate regression analysis. This section describes the statistical test involved in multivariate regression analysis.

4.5.1 R-square and Durbin Watson test

The first test in regression is R-square to measure the model fit. The R-squared is a statistical measure that indicates how much of the variation of a dependent variable is explained by an independent variable in a regression. R-squared, a statistical measure, quantifies the proportion of variance in the dependent variable explained by the independent variables in a regression model. Henseler (2009) proposed a rule of thumb for acceptable R² with 0.75, 0.50, and 0.25 are described as substantial, moderate, and weak respectively.

The R-squared and adjusted R-squared are statistics derived from analyses based on the general linear model. It represents the proportion of variance in the outcome variable which is explained by the predictor variables in the sample (R-squared) and an estimate in the population (adjusted R-squared). The coefficient of determination, R², is a measure of how well the regression model describes the observed data.

One of the assumptions of regression is that the observations are independent. The Durbin Watson (DW) statistic is a test for autocorrelation in the residuals from a statistical model or regression analysis. The Durbin-Watson statistic will always have a value ranging between 0 and 4 (Dale and Fortin, 2009). If there is no autocorrelation, the Durbin-Watson statistic should be between 1.5 and 2.5.

Table 5 shows the value of the Durbin-Watson test is 2.372. This value is between 1.5 and 2.5. Therefore, this indicates there is no serious autocorrelation problem in the data set.

Table 5: Model summary

Model	R	R-square (R ²)	Goodness of Model (R ² >0.5)	Durbin Watson test	Autocorrelation (1.5<DW<2.5)
1	0.834	0.695	Yes	2.372	No autocorrelation

Predictors: (Constant), Service_Quality, System_Quality, Information_Quality

Dependent Variable: Adoption

4.5.2 F-test for data fit analysis

The F-ratio in the ANOVA Table 6 tests whether the overall regression model is a good fit for the data. The ANOVA (Analysis of Variance) is used to look at how well the predictors as a whole can account for differences in the response variable (Nelson et al., 1979). The variability in the response variable is partitioned between different explanatory components.

Table 6 shows that the independent variables statistically significantly predict the dependent variable, $F (3, 96) = 72.979$, $p < .05$. The null hypothesis is that there is no linear relationship between the predictors and the response variable. Therefore, it has sufficient evidence to reject the null hypothesis. The p-value is 0.000 which is less than 0.05, this indicates the regression model is a good fit for the data.

Table 6: Model fit analysis

Model 1	Sum of squares	df	Mean square	F	Significant (p-value)	Good fit (p<0.05)
Regression	33.562	3	11.187	72.979	0.000	Yes
Residual	14.717	96	.153			
Total	48.279	99				

Dependent Variable: Adoption

Predictors: (Constant), Service_Quality, System_Quality, Information_Quality

4.5.3 Coefficient of Multiple Linear Regression

Multiple linear regression is a model for predicting the value of one dependent variable based on two or more independent variables (Jobson, 1991). Multiple linear regression involves finding the best-fitting surface of a suitable functional form that relates the values of explanatory variables, and the mean value of a response variable. The multiple linear regression (MLR) method helps in establishing the relationship between the independent and dependent variables. MLR is a method used to estimate the size and statistical significance of the relationship between a dependent variable and independent variables. MLR is the regression method that is used to establish linear relationships between multiple independent variables and the dependent variable that is influenced by them (Alexopoulos, 2010).

Table 7 shows the multiple linear regression for this study. There are three independent variables involved in this study namely Information Quality, System Quality, and Service Quality. For the first independent variable, the standardized beta is 0.396. Therefore, an increase of one standard deviation in Information Quality (IV1), and a 0.396 standard deviation increase in Adoption (Y) of digital platforms for distance learning. The p-value is 0.000 which indicates there is a significant influence of Information Quality (IV1) towards Adoption (Y) of digital platforms for distance learning.

For the second independent variable, the standardized beta is 0.373. Therefore, the increase of one standard deviation in System Quality (IV2), and a 0.373 standard deviation increase in Adoption (Y) of digital platforms for distance learning. The p-value is 0.000 which indicates there is a significant influence of System Quality (IV2) towards Adoption (Y) of digital platforms for distance learning.

For the third independent variable, the standardized beta is 0.354. Therefore, the increase of one standard deviation in Service Quality (IV3), and a 0.354 standard deviation increase in Adoption (Y) of digital platforms for distance learning. The p-value is 0.000 which indicates there is a significant influence of Service Quality (IV3) towards Adoption (Y) of digital platforms for distance learning.

Table 7: Multiple linear regression

Independent variable	Unstandardized b	Standardized Beta	t-statistic	p-value	Effect Significant
Constant	-.266		-1.027	0.307	
IV1: Information Quality	.372	.396	6.470	0.000	Yes
IV2: System Quality	.349	.373	6.106	0.000	Yes
IV3: Service Quality	.389	.354	5.593	0.000	Yes

Dependent Variable: Adoption

4.5.4 Multicollinearity Checking for Regression Model

Regression analysis encounters multicollinearity when two or more predictor variables have a high degree of correlation and do not contribute distinct or independent information to the regression model. If the correlation between the variables is strong enough, it may be difficult to fit and comprehend the regression model.

One way to detect multicollinearity is by using a metric known as the variance inflation factor (VIF), which measures the correlation and strength of correlation between the predictor variables in a regression model. Detecting multicollinearity is important because while multicollinearity does not reduce the explanatory power of the model, it does reduce the statistical significance of the independent variables. Variance inflation factors were checked for every explanatory variable used in the model and need to be lower than 5, the usual cut-off value used to check for multicollinearity issues (Miles 2014).

A value of 1 indicates there is no correlation between a given predictor variable and any other predictor variables in the model. A value between 1 and 5 indicates a moderate correlation between a given predictor variable and other predictor variables in the model, but this is often not severe enough to require attention. A value greater than 5 indicates a potentially severe correlation between a given predictor variable and other predictor variables in the model. In this case, the coefficient estimates and p-values in the regression output are likely unreliable.

Table 8 shows the VIF multicollinearity test for three independent variables. A value larger than 5 shows the existence of serious multicollinearity. Table 8 shows the VIF for IV1 is 1.181, IV2 is 1.172, and IV3 is 1.262. These values are less than 5. Therefore, all three variables are free from serious multicollinearity problems.

Next, a condition index shows the degree of multicollinearity in a regression design matrix. Kennedy (2003) describes a condition index as the largest to the smallest characteristic root of $X'X$; it's a measure of how close $X'X$ is to the perfect multicollinearity (called singularity). A condition index with larger than 30 indicates serious multicollinearity (Snee, 1983). Table 9 shows the three independent variables do not exhibit serious multicollinearity problems.

Table 8: Multicollinearity test

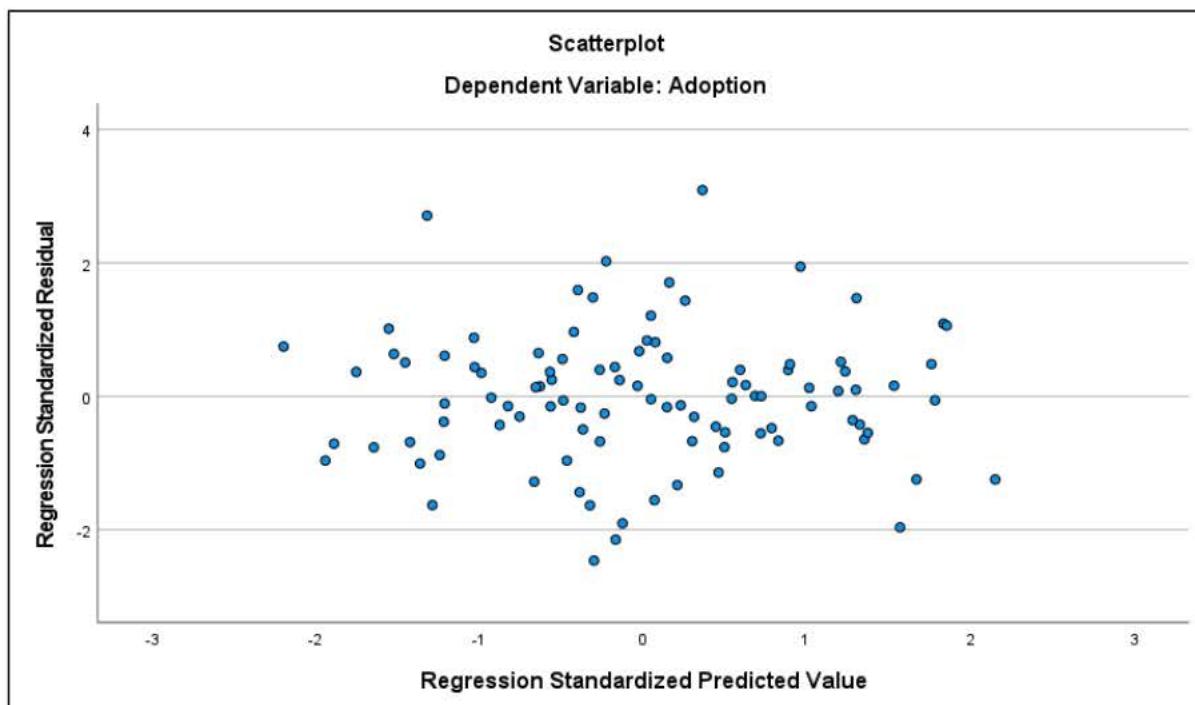
Independent variable	Collinearity Statistics		Serious multicollinearity (VIF>5)
	Tolerance	VIF	
IV1	.847	1.181	No
IV2	.853	1.172	No
IV3	.792	1.262	No

Table 9: Multicollinearity test

Dimension	Condition Index	Variance proportion (VP)			Multicollinearity (VP=0.9)
		IV1	IV2	IV3	
1	1.000	.00	.00	.00	No
2	10.914	.51	.64	.00	No
3	12.965	.42	.30	.58	No
4	15.286	.07	.06	.41	No

4.5.5 Residual diagnostics

Next, this study evaluated the homoscedasticity of the data set. Homogeneity of variance (homoscedasticity) indicates the error variance should be constant. Figure 2 shows the residual that the trend is centered around zero but also that the variance around zero is scattered uniformly and randomly. Figure 3 shows the histogram for standardized residual. The distribution of data follows a normal curve. The mean is 0, and standard deviation is 0.985. This proved the data follow homoscedasticity distribution.


Figure 2: Scatter plot for residual

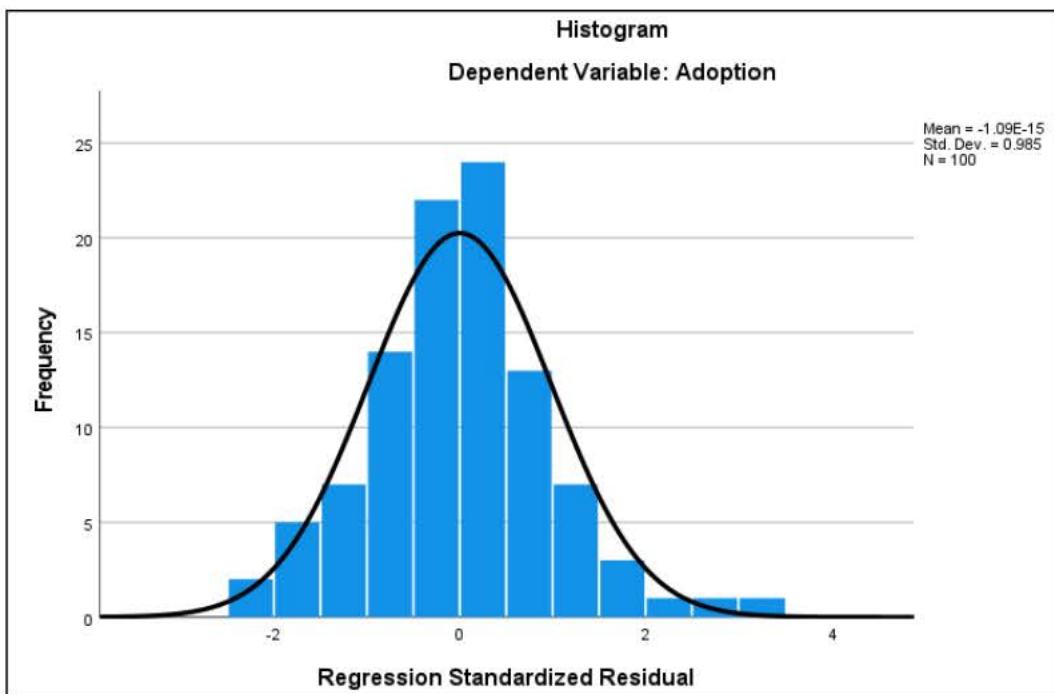


Figure 3: Histogram of residual

This study also checked for outliers. The Mahalanobis distance measures distance relative to the centroid. The centroid is a base or central point that can be thought of as an overall mean for multivariate data. Any p-value that is less than .001 is considered to be an outlier. In this study, no data exhibits a p-value less than 0.001. Therefore, there is no outliers exist in the data set.

5. Conclusion

This study aims to evaluate the student adoption of digital platforms for distance education. The population is university students who registered for distance education programs. The number of the sample is 100. The main findings of this study are:

- i. This study uses the Information Systems Success Model (ISSM) as the underpinning theory. There are three independent variables: Information Quality, System Quality, and Service Quality.
- ii. The first hypothesis is supported which indicates there is a significant influence of Information Quality (IV1) towards student adoption of digital platforms for distance learning. The p-value is 0.000 with a t-statistic is 6.470.
- iii. The second hypothesis also is supported which explains there is a significant influence of System Quality (IV2) towards student adoption of digital platforms for distance learning. The p-value is 0.000 with a t-statistic is 6.106.
- iv. Next, the third hypothesis is supported by proving that there is a significant influence of Service Quality (IV3) towards student adoption of digital platforms for distance learning. The p-value is 0.000 with a t-statistic is 5.593.

The contribution of this study is, that it helps university management to adopt an optimal approach to developing an ecosystem for digital distance education. This study also contributes to the advancement of knowledge in the area of distance learning acceptance among students using the Information Systems Success Model (ISSM) as underpinning theory.

This study can be extended to include more significant variables by combining the theoretical framework. At the same time, the sampling can be increased to a larger audience in Malaysia. In addition, second source data also can be included to improve the efficiency of data analysis and findings.

Acknowledgment

The authors would like to thank the Universiti Utara Malaysia (UUM) for providing support for this study [Geran Penjanaan UUM, SO Code 14908].

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