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Best Predictor of Cloud Computing Usage among Various Constructs

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ABSTRACT This study aimed to analyse the determinants of Cloud computing adoption and use among high school learners. The research question that followed was; which is the best predictor of Cloud computing usage given a set of determinants? The study involved 116 respondents using simple random sampling. The results revealed that performance expectancy was the strongest predictor of the intention to adopt Cloud computing when compared to other constructs. There was a strong positive correlation of r = +0.989 between 'the use of Internet for learning purposes in enhancing the effectiveness of learning' and 'being taught in their studies through Internet devices'. These findings suggest that Cloud computing adoption and application may be enhanced through educating teachers and learners on the potential benefits of this mode of communication in improving the accessibility and dissemination of scholarly content.

INTRODUCTION

With the evolution and development of complementary information and communication technologies, Cloud computing has been regarded as a new paradigm for hosting information technology (IT) infrastructure. Cloud system adoption assumes that schools partially or fully replace their landscapes of incumbent system with cloud environment. With the elastic provision of computing resources, Cloud systems can be automatically upgraded and can be flexibly scaled upward and downward (Gill 2011).

Davies (2012) explored whether interactive technologies provide opportunities for new literacy practices through text making; the research considered how teenagers use the site to present themselves and "do friendship". Davies (2012) furthermore, examined the relationship between frequency of Facebook use, participation in Facebook activities and student engagement. The study findings indicated that Facebook use was significantly predictive of engagement scale score and of time spent in co-curricular activities.

One of the barriers to the adoption of Cloud computing as a learning tool could be students' perceptions regarding technology use in personal space versus learning spaces. Most students rarely use social media for educational purposes because they tend to separate their social life (pleasure) from their learning (Rodriguez et al. 2014).

In order to avoid possible risks of system adoption, schools have a tendency to behave conservatively when it comes to new technology and maintain the old systems. For instance, the associated investments on existing system will impede learners to chase new IT innovations. Therefore, identifying the determinants of cloud systems adoption and resistance has substantial merit for helping researchers and managers to have a better understanding on this growing new IT paradigm.

This study might be used to design teacher training (pre-service and in-service). This could help to foster Internet use in effective and meaningful ways, which might enhance student learning. This research will contribute towards the design of a contextual model for the adoption and application of technology for learning, and the outcomes of this research hold important implications for policy and practice regarding Internet services at the school level.

Literature Review and Theoretical Framework

This study is based on the Unified Theory of Acceptance and Use of Technology (UTAUT), which has four core determinants that influence behavioural intention (BI) to use a technology; these determinants are defined as follows (Venkatesh et al. 2003). Performance expectancy (PE): the degree to which an individual believes that using the system will help him or her to attain gains in performing certain activities; Effort expectancy (EE): the degree of ease associated with use of the system; Social influence (SI): the degree to which an individual perceives that important others believe he or she should use the new system; and Facilitating conditions (FC): the degree to which an individual believes that the school and technical infrastructure exist to support the use of a system.

The UTAUT was originally created in order to understand the factors that influence employee information technology acceptance and use. Nevertheless, several studies have applied it to an educational context. In this latter regard, UTAUT has been applied in technologies such as mobile learning (Wang et al. 2009), computer based assessment (Terzis and Economides 2011), e-learning systems (Chen 2011) and web 2.0 (Huang et al. 2013). Traditionally, the UTAUT model and its application assume that all factors directly affect the intention to use an information technology (Rodriguez et al. 2014).

Venkatesh and Davis (2000) argue that the performance expectancy construct is the strongest predictor of intention, and remains significant at all points of measurement in both voluntary and mandatory settings consistent with previous model tests.

Collis and Meeuwsen (1999: 27) state, it is obvious that learners lack the specific "learning to learn" skills. By making use of guidelines gathered from Collis and Meeuwsen (1999: 27) five areas were identified where there are shortcomings and which need to be developed in order to expand the "learning to learn" principle (see recommendations).

Collis and Meeuwsen (1999: 32) refer to Young (1997: 41) suggesting a scaffolding process where learners cross the divide between individualised-learning and assisted-learning. Four strategies are identified by Young. They are opportunities for completing assigned tasks through joint networking with other learners (to counter the negative effect of uninvolved learners). These are opportunities for learners, not only to assess but also to think at more length than in the past on their schoolwork and study material. Increasing learners' responsibility in planning and carrying out the didactic process and being expected to set out procedures and practice clearly.

From a theoretical point of view, the assumption is that, the relationship between performance expectancy and intention will be moderated by gender and age. Research on gender differences indicates that men tend to be highly task-oriented (Minton and Schneider 1980) and, therefore, performance expectancies, which focus on task accomplishment, are likely to be especially salient to men. Gender schema theory suggests that such differences stem from gender roles and socialisation processes reinforced from birth rather than biological gender per se (Lynott and McCandless 2000).

Fowler and Worthen (as cited in Behrend et al. 2011) note that, with cloud computing emphasis on the delivery of free applications anywhere, it is a promising prospect for educational institutions faced with number of constraints, including technical, budgetary restrictions and mobile learner population. Successful implementation of Cloud computing in educational settings, however, requires careful attention to a number of determinants from both the learner and the school perspective. The emphasis on the delivery of low-cost or free Cloud computing, the need for Cloud computing in educational settings coupled with the number of determining factors form the crux of the current study.

Research Question

This paper addresses the following research question as it emanates from the problem:

- Which is (are) the best predictor(s) of Cloud computing usage given a set of determinants?

METHODOLOGY

A quantitative approach based on positivist paradigm was used for the measurement of data, in order to determine the effect that the independent variables (performance expectancy, effort expectancy, confounding variables, and social influence) have on Cloud computing adoption and use. One school was selected in the East London district purposively; however, the respondents were selected using simple random sampling technique.

The survey instrument used for this research was developed by the researcher based on established procedures in literature. The survey instrument contained five sections. Section A comprised six questions and it focused on demographic information of learners: gender, age, grade, residential area, the kind of Internet devices they had, and major subjects taken at school. Section B was designed to know the ability of learners in using the Internet. The section contained 15 items which required the respondents to either select a 'yes' or a 'no'. Section C focused on the learners' use of Internet for learning purposes, in this section they had to tick all the activities they have done before. Section D, which contained 30 items focused on performance expectancy, effort expectancy, perceptions, price of Internet, persistent use, and behavioural intention. A Likert scale of Strongly Agree (SA), Agree (A), Disagree (D) and Strongly Disagree (SD) was used. Section E of the questionnaire contained three items which addressed the usage frequency of SMS, MMS, and ringtone and logo download by learners. The response modes were: 'Never' (N); 'Rarely' (R); 'Often' (O); and 'More often' (MO).

To test the instrument's validity and reliability, the initial draft was administered on 15 learners drawn from a high school in the East London district. The feedback obtained from this pilot study was used to revise the final questionnaire. The final instrument was tested for reliability using Cronbach's Alpha reliability statistics. The reliability measurements obtained for the five sections of the instrument were $\alpha = 0.987$ (performance expectancy), $\alpha = 0.878$ (effort expectancy), $\alpha = -0.525$ (learners' demographics), $\alpha = 0.857$ (Internet self-efficacy), and $\alpha = 0.834$ (experience in using Internet devices). Two hundred and eighty six copies of the questionnaire were distributed to randomly selected learners after the teaching time. The questionnaire was administered on the sample during the first semester of the 2013 school term (March – April 2013). One hundred and sixteen copies were returned, and the return rate was therefore 40.6%.

The responses of the respondents were tabulated and compared after the standardised beta coefficient from the regression analysis was performed. The analysis was done to present the details about the best predictor of Cloud computing among the main constructs of the UTAUT.

Ethical Measures

Adolescent-learners were used in this research. Since these individuals are minors their parents or guardians, acted in loco parentis, to consent to their participation. All participation in the study was voluntary. Respondents were informed about the nature of the study and given a choice to choose to participate or not. Only individuals who volunteered were allowed to participate. Privacy and confidentiality of participants was guaranteed. The identity of the respondents and the research site were not revealed in the reporting of the findings. Thus, personal details from respondents remained anonymous. The researchers had to obtain ethical clearance from the Higher Degrees Committee before commencing with the research.

RESULTS

The construct tied to usefulness, namely performance expectancy, has consistently been shown to be the strongest predictor of behavioural intention (Venkatesh et al. 2003). Among the four main constructs assessed in this study, performance expectancy was the strongest determinant of Cloud computing adoption and application. When comparing the correlation values with other main constructs, performance expectancy had positive correlations and mostly large correlations.

To address the research question in this study, a multiple linear regression analysis was performed to determine the best predictor of Cloud computing usage given a set of determinants (performance expectancy, effort expectancy, social influence, and facilitating conditions). The construct tied to usefulness, namely performance expectancy, has consistently been shown to be the strongest predictor of behavioural intention (Venkatesh et al. 2003). Among the four main constructs assessed, performance expectancy was the strongest determinant of Cloud computing adoption and application.

As shown in Table 1, the model summary provides an overview of the results for performance expectancy. Of primary interest are the R Square and Adjusted R Square values, which are 0.074 and -0.015, respectively. The weighted combination of the predictor variables explained approximately 1% of the variance of behavioural intention. The loss of so much strength in computing the Adjusted R Square value is primarily due to a relatively small sample size combined with a relatively large set of predictors. Using the standard regression procedure where all of the predictors were entered simultaneously into

Table 1: Model summary

Model	R	R square	Adjusted R square	Std. error of the estimate	Change statistics R Square change	F change	df1	df2	Change statistics Sig. F change
1	.271[a]	.074	-.015	1.059	.074	.834	10	105[a]	.597

the model, R Square Change went from zero before the model was fitted to the data to 0.074 when the variable was entered.

In Table 2, the Zero-order column under the correlations lists the Pearson *r* values of the dependent variable (intention to use Cloud computing) with each of the predictors. The Partial column under the correlations lists the partial correlations for each predictor as it was evaluated for its weighting in the model (the correlation between the predictor and the dependent variable when the other predictors are treated as covariates). The Part column lists the semi partial correlations for each predictor once the model is finalised; squaring these values informs the researcher of the percentage of variance each predictor uniquely explains. For example, (PE4) to use Internet for learning purposes in enhancing the effectiveness of learning accounts for about 2% of the variance of behavioural intention (-0.121* -0.121 = 0.0146 or approximately 0.02) given the other variables in the model.

The raw regression coefficients are *partial regression coefficients* because their values take into account the other predictor variables in the model; they inform us of the predicted change in the dependent variable for every unit increase in that predictor. For example, PE2 is associated with a partial regression coefficient of 0.933 and signifies that for every additional point on the PE2 measure, one would predict a gain of 0.933 points on the intention to continue using mobile Internet in the future measure. As another example, PE9 is associated with a partial regression coefficient of -0.504 and signifies that for every additional point on the PE9 measure, the researcher would predict a decrease of 0.504 points on the intention to use Cloud computing measure.

Regression Assumption Results

Linearity

In the lack of fit test from Table 3, the probability of the F test statistic (F = 0.399) was p = 0.979, greater than the alpha level of significance of 0.05. The alternative hypothesis that "a linear regression model is appropriate" was not rejected. The null hypothesis that "a linear regression model is not appropriate" was not supported by this test. In other words, failure to reject the alternative hypothesis satisfied the assumption of linearity.

Table 2: Regression analysis coefficients for performance expectancy[a]

Model	Unstandardized coefficients Beta	Unstandardized coefficients Std. error	Standardized coefficients Beta	t	Sig.	Zero-order	Partial	Part
Constant	2.117	.227		9.338	.000			
PE1	.212	.542	.289	.391	.697	-.113	.038	.037
PE2	.933	.724	1.204	1.288	.200	-.085	.125	.121
PE3	-.371	.485	-.435	-.764	.446	-.135	-.074	-.072
PE4	.167	.376	.194	.444	.658	-.121	.043	.042
PE5	-.243	.341	-.298	-.714	.477	-.137	-.070	-.067
PE6	-.319	.543	-.446	-.588	.558	-.129	-.057	-.055
PE7	-.667	.559	-.867	-1.193	.236	-.098	-.116	-.112
PE8	.467	.510	.628	.916	.362	-.080	.089	.086
PE9	.504	..605	-.697	-.833	.406	-.111	-.081	.078
PE10	.221	.529	.298	.418	.677	-.124	.041	.039

[1]a. Dependent Variable: I intend to continue using mobile internet in the future

Table 3: Lack of fit test for performance expectancy (Linearity)

Source	*Sum of squares*	*df*	*Mean square*	*F*	*Sig.*
Lack of fit	7.895	16	.493	.399	.979
Pure error	109.949	89	1.235		

Independence

In Table 4, the Durbin-Watson statistic for this problem is 2.17, which falls within the acceptable range from 1.50 to 2.50 (from Table 2). The analysis satisfied the assumption of independence of errors.

Normality

In evaluating normality for performance expectancy, this study used the skewness statistics to check if values obtained were both within the range of acceptable values from -1.0 to +1.0. In Table 5, the values obtained met this assumption of normality. The null hypothesis that "the distribution of the residuals is normally distributed" was not rejected. The acceptance of the alternative hypothesis in this study satisfied the assumption of normality of errors.

The research hypothesis that "the distribution of the residuals is not normally distributed" was not supported.

Homogeneity

As shown in Table 4, the largest sample standard deviation (1.47310) divided by the smallest sample standard deviation (1.22015) is not greater than two (1.21). Therefore, the assumption that the population variances are equal has been met.

Performance expectancy met all the four linear regression assumptions as discussed. Since there were no violations, this independent variable was found to be influential on the learners' intention to adopt and use Cloud computing.

DISCUSSION

Cell phones, the Internet, and computers all aid in continuing relationships with families, learners, and teachers. The results of this study are in contrast to Subrahmanyam and Greenfield (2008: 136), who noted that new media may be "depersonalizing the process of interpersonal communication". Instead of viewing new media as another means to boost communication between close family and peers, Subrahmanyam and Greenfield (2008) suggested that it may be negatively affecting face-to-face communication because of new media's overwhelmingly impersonal attributes.

The Beta (standardised regression coefficients) values were also used to measure how strongly each predictor variable influences the

Table 4: Durbin-Watson test for performance expectancy (independence) model summary[b]

Model	*R*	*R square*	*Adjusted R square*	*Std. error of the estimate*	*Durbin-Watson*
1	.271[a]	.074	-.015	1.059	2.172

Table 5: Descriptive statistics for performance expectancy sub variables

Sub variabless	*N statistic*	*Mean statistic*	*Std. error*	*Std. deviation statistic*	*Variance statistic*	*Skewness statistics*	*Std. error.*	*Kurtosis statistic*	*Std. error*
PE1	116	2.6897	.13324	1.43505	2.059	-.246	.225	-1.896	.446
PE2	116	2.3362	.12603	1.35739	1.843	.258	.225	-1.769	.446
PE3	116	1.9914	.11453	1.23356	1.522	.780	.225	-1.083	.446
PE4	116	1.8448	.11329	1.22015	1.489	1.004	.225	-.744	.446
PE5	116	2.3103	.11960	1.28817	1.659	.492	.225	-1.273	.446
PE6	116	2.6724	.13677	1.47310	2.170	-.162	.225	-1.891	.446
PE7	116	2.3793	.12704	1.36831	1.872	.216	.225	-1.803	.446
PE8	116	2.4052	.13129	1.41408	2.000	.206	.225	-1.823	.446
PE9	116	2.3621	.13491	1.45301	2.111	.383	.225	-1.566	.446
PE10	116	2.1552	.13165	1.41792	2.010	.689	.225	-1.197	.446

criterion variable. The beta was measured in units of standard deviation. For example, a beta value of 2.5 indicates that a change of one standard deviation in the predictor variable will result in a change of 2.5 standard deviations (SD) in the criterion variable (from Table 2). Thus, the higher the beta value the greater the impact of the predictor variable on the criterion variable.

The respondents found 'the use of Internet for learning purposes saving them a lot of time' more favourable (M = 2.6897, SD = 1.43505), than when performance expectancy was attributed to 'more interest in study if Internet devices are used' (M = 2.6724, SD = 1.47310), or 'the ease of learning because of the owning of Internet devices would allow them to study anytime and everywhere' (M = 2.4052, SD = 1.41408).

The respondents found 'the use of Internet devices entertaining in their study' more agreeable (M = 2.3793, SD = 1.36831) than when performance expectancy was ascribed to 'The use of Internet for learning purposes in enhancing the effectiveness of their learning' (M = 2.3362, SD = 1.35739) or 'the encouragement to learn if they could access materials anytime anywhere via mobile devices' (M = 2.3621, SD = 1.45301).

The respondents strongly agreed to 'more desire they would have to use mobile devices as a way for learning' (M = 2.1552, SD = 1.41792) than when performance expectancy was credited to 'Mobility which enables them to accomplish tasks quickly' (M = 1.9914, SD = 1.23356) or 'knowing that mobile devices are also mediums for learning' (M = 1.8448, SD = 1.22015).

The researchers bore in mind that in simple linear regression the Pearson's r is the beta weight of the predictor, yet in combination with the other predictors it is not a significant predictor in the multiple regression model. The reason is that its predictive work is being accomplished by one or more of the other variables in the analysis (Statistics Solutions 2013). The point here is that, just because a variable receives a modest weight in the model or just because a variable is not contributing a statistically significant degree of prediction in the model, it is not a reason to presume that it is itself a poor predictor.

The Y intercept of the raw score model was labelled as the constant and had a value of 2.117 which was the highest among other dependent variable (from Table 2).The implication of these results is that the majority of the learners at the school generally supported performance expectancy as a determinant of Cloud computing adoption and use. These findings therefore suggest that improving factors that affect learners' behavioural intention to adopt and use Cloud computing for learning purposes will ultimately increase the adoption of this mode of academic communication.

In this study, there are 115 (N - 1) total degrees of freedom with 10 predictors as illustrated on Table 2. The main important point about regression analysis, which this study employed, is that, a highly predictive variable could be left out in the cold, being sacrificed for the good of the model (Statistics Solutions 2013). The researchers noted that, independent variables could correlate substantially with one another, more especially if there is only one predictor it would have a different beta weight. The Regression effect was statistically insignificant indicating that prediction of the dependent variable is not accomplished better than can be done by chance. However, when a correlation analysis was conducted to examine the strength of association among the ten sub variables, a large positive correlation was found between all the dependant variables. All the sub variables were significant at the level of $p < 0.05$.

Hence, performance expectancy was detected as the best predictor of the intention for learners to adopt and use Cloud computing. Collis and Meeuwsen (1999: 32) refer to Young (1997: 41) suggesting a scaffolding process where learners cross the divide between individualised-learning and assisted-learning. Some benefits of Cloud computing are identified by Young (1997). They are opportunities for completing assigned tasks through joint networking with other learners (to counter the negative effect of uninvolved learners).

CONCLUSION

The linear regression assumptions were met for this predictor (performance expectancy) as discussed. Since there were no violations of the linear regression assumptions, performance expectancy was also found to be the best predictor of Cloud computing compared to other constructs.

The use of Internet devices appears to be a more efficient means of communication that, at times, displaces traditional media. These conclusions are an indication that normally adjusted adolescents use the Internet as another tool for communication. Learners are reinforcing relationships and having positive experiences when using the Internet as alluded in the discussion of this study.

RECOMMENDATIONS

These are opportunities for learners, not only to assess but also to use Internet devices at more length than in the past on their assignments and studies. Increasing learners' responsibility in planning and carrying out the didactic process and being expected to set out procedures and practice clearly. Cultivating a wide range of study habits and skills, in order to deal with identified information and to achieve best learning results. Developing linkages between the subject matter being studied and related material from various sources and, finally progressing to a stage of self-reflection whereby the learner is able to identify areas of weakness or deficiencies in knowledge and seek ways to counter these outside the normal examination system.

PRACTICAL IMPLICATIONS

Although this study focused on learners, but it has implications for teachers and parents to remain current with educational developments. Parents need to be well informed about the needs of the real world and about what is required to develop their children into meaningful contributors to it, so that they as parents can be included by exposing them to the new methodologies and become more efficient in their role that they must fulfil in their children's education.

Successful technological implementations should largely depend upon the motivation, knowledge, and skill of administrators and teachers to implement and utilise technology in effective ways to enhance learning for all learners. It is imperative that these teachers be fully supported in this regard through adequate pre-service preparation, on-going and state-of-the-art in-service activities, and links to local universities and other resources for additional support and learning.

NOTE

1. PE1 = The use of Internet for learning purposes would save the me a lot of time. PE2 = The use of Internet for learning purposes would enhance the effectiveness of the my learning. PE3 = Mobility enables me to accomplish tasks quickly. PE4 = I know that mobile devices are also mediums for learning. PE5 = Unexpected problems could be fixed at the first time of using Internet devices. PE6 = I would feel more interested in study if I could use Internet devices. PE7 = I would be entertained in my study by using Internet devices. PE8 = Owning an Internet device would ease my learning because it would allow me to study anytime, anyplace. PE9 = I would be more encouraged to learn if I could access materials anytime anywhere via mobile devices. PE10 = I would have more desire to use mobile devices as a way for learning.

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