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Application of the Theory of Diffusion of Innovation on the Adoption of Automated Teller Machines in the Sunyani Municipality

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Abstract: The ongoing debate concerning economic losses associated with human tellers and the negative impact of queuing in the banking halls have led to new technologies and innovation diffusion. This paper applied a regression model in which end-user's level data were analyzed in order to predict adoption of automated teller machines using theory of diffusion of innovation (e.g., relative advantage, complexity, observability, trialability and compatibility) empirically. Applying the principal component analysis and regression as analytical techniques, the results were compatible with adoption intention. Following from the PCA, the results show that the cumulative percentage of the predictive variables were above the 50% threshold with KMO measure and Cronbach Alphas recording scores above 70%, suggesting the appropriateness of PCA in data reduction. The predictive variables have strong predictability and were significant. Abstracting from the results there may be two reasons relating to the low adoption decisions. The first reason may be due to some inherent inefficiencies or unwarranted phenomenon which may have lessen patronage and secondly, customers' categorization on the basis of innovativeness which skewed in favour of early adopters than late adopters. The banks should take steps to update the existing technologies relating to automated teller machine operations in particular in order to address the challenges before enforcing any future deployment to meet end-users' expectations. Because adoption can be influenced by customers categorization on the basis of innovativeness, analysis of these groupings should be conducted in order to understand the characteristics of each group.

Keywords: Adoption, relative advantage, innovators, late majority and laggards

1. INTRODUCTION

Banks continue to differ in many ways with respect to business models, growth strategies or financial health. With the advancement of technology automated teller machines have paved way for new banking innovation that have replaced the traditional practices such that difficulties faced by customers have been minimized to a great extent. The adoption of technology such as ATM by customers is a critical component of the use of Information and Communication Technology (ICT) and as a result, the Technology Acceptance Model (TAM) has widely been applied to examine the underlying antecedents in determining end-users' behavioral intention to use such technologies (Baraghani, 2007). And when investigating the use of ICT-related innovations, intention-based models have provided important information about users' behavioral intention in determining their adoption rate (Lee et al., 2021). Automated Teller Machines (ATMs) have been extensively deployed by banks within the municipality in order to facilitate flexible banking services, but their use appear largely underutilized as long queues remained noticeable in banking halls exerting pressure on human tellers at peak periods. Again, it appears that users' perception about this innovation is mixed and their patronage is not too clear. Clearly the emerging scenarios pose potential adoption problems for the banks regarding the degree to which willingness to use automated teller machines fluctuates widely. It is important to determine why this is happening. Since the automated teller machines offer alternative to queues in the banking halls, there is a need to understand the patronage of the devices from the perspective of users' judgment. This is because the use of teller machines can be specifically perceived through customers' attitude and action. The paper develops an extended the theoretical model to investigate users' adoption based on Technology Acceptance Model by integrating diffusion of innovation theory developed by Rogers (2003) to examine factors which influence users' behavioral intentions. It is also examined adopter categorization on the basis of innovativeness among five (5) universal banks in the Sunyani Municipality.

2. LITERATURE

Technology Acceptance Model (TAM)

Technology Acceptance Model (TAM) has received considerable attention and empirical support for the past decade (Davis et al., 1989). The model which explained the acceptance of information systems by users states that the acceptance of a given technology is influenced by the users' behavioral intention, which is in turn determined by the perception of its usefulness in performing the task and perceived ease of its use. This hypothesis has emphasized that acceptance and use of information technologies can bring benefits to the end-user such as enhanced performance and efficiency (Sharda et al.,1988). The model thus provided the processes underlying the acceptance theory to explain behaviour and theoretical explanation for the successful implementation of a technology or innovation. The basic assumption is that the end-user's belief predicts the innovation acceptance. And since the pioneering works of Davis, 1989, various technology acceptance models and theories have been applied, including the theory of planned behaviour (Ajzen 1991), Theory of Reasoned Action (Fishbein & Azjen 1975), TAM2 (Venkatesh & Davis 2000), Unified Theory of Acceptance and Use of Technology (Venkatesh et al. 2003) and TAM3 (Venkatesh & Bala 2008; Venkatesh et al., 2012). Al-Emran and Granić (2020) concluded that the extension of the model is still plausible across various disciplines in order to predict user's technology adoption behaviours by examining beliefs and attitudes of end-users towards the technology and can be applied to evaluate the desire of a customer to use any technology systems (Zhan et al., 2018; Singh & Srivastava 2020)

Theory Extensions
The Technology Decision Process Model

Given the expansionary work and increasing prominence of the TAM to fully capture the nature of the processes under consideration (Davis,1986) over time, empirical examination of newly developed models has emerged to address the gap in the literature concerning additional factors influencing acceptance of technology (Gefen et al., 2003). According to Rogers (2003), the term adoption is a decision of "full use of technology as the best course of action available" and rejection is a decision "not to adopt an innovation". Diffusion is "the process in which an innovation is communicated through certain channels overtime among the members of a social system", this can be expressed in terms of the innovation, communication, time and social system of the diffusion of innovation. Rogers (2003), then described the innovation-decision process as "an information-seeking and information activity, during which people are influenced to minimize their doubt and uncertainty about the advantages and disadvantages about the innovation. The innovation-decision process includes the following: (i) knowledge, (ii) persuasion, (iii) decision, (iv) implementation and (v) confirmation. These stages typically follow each other in a time-ordered manner. Rogers (2003) described the innovation-diffusion process as “an uncertainty reduction process” and proposed attributes of innovation which may minimize the degree of uncertainty about the innovation including: Relative advantage, compatibility, complexity, trialability and observability. Accordingly, individual perception of these attributes predicts their rate of adoption. The rate of adoption is defined as “the relative speed with which an innovation is adopted my members of a social system” For instance, the number of individuals who adopted the innovation for a period of time can be measured as the rate of adoption of the innovation. The perceived attributes of an innovation are significant predictive variables of the rate of adoption. Rogers (2003) concluded that 49-87% of the variance in the rate of adoption can be explained by these five attributes-which can help identify weaknesses to be addressed when improving innovation perception of customers behaviour. Behavioral intention is defined as the readiness of an individual to perform a given behaviour (Ajzen, 2002) and Ravichandran et al (2010) observed that service quality such as responsiveness, empathy and tangibility are predictive variables influencing such behaviour.

End-User Categorization

Diffusion theorists argued that a population regarding a particular technological innovation can be grouped into five segments based on their propensity to adopt a specific innovation. The proponents maintained that the adopter categories as “the classification of members of a social system” on the basis of innovativeness may define the rate of adoption and these include: innovators, early adopters, early majority, late majority and laggards. Each group has its own “personality” at least as far as its attitude to a particular innovation goes. In each adopter segment, individual is similar in terms of their innovativeness – refers to the degree to which an individual or other units of adoption is relatively earlier in adopting the new idea than other members of the system. Braak (2001) argued that innovativeness is a relative-stable, socially constructed, innovation-dependent characteristic which show an individual’s willingness to change their familiar practice. Thus, innovativeness is very useful in understanding the desired behaviour in the innovation-decision process. The categorization of the adopters is based on innovativeness using the normal distribution curve and it is only adopters of successful innovation can generate this curve overtime. In this normal distribution curve, each category is defined using the standardized percentage of respondents. For instance, the area lying under the left side of the curve and two standard deviation below the mean includes innovators who adopt innovation as the first 2.5% of the individuals in the system, followed by area lying under the left side of the curve on standard deviation below the mean includes early adopters who adopt innovation as the second 13.5% of the individuals in the system, followed by area lying under the left side of the curve below the mean includes early majority as the third 34.0% of the individual in the system, followed by area lying under the right side of the curve and one standard deviation above the mean includes late majority who adopt innovation as the forth 34.0% of the individual in the system and finally followed by area lying under the right side of the curve and two standard deviation above the mean includes the laggards who adopt innovation as the fifth 16.0%.

Technique and Conceptual Model

In our study a parametric analytic technique for the evaluation of the attributes of theory of diffusion of innovation such as adoption of teller machine was applied. Specifically, we employ logistic regression model to measure the influence of five construct in order to predict adoption. The technique’s major advantage is that it deals with the case of the probability of adoption and multiple constructs which are not controlled by end-users. The application of the technique facilitates the estimation of relationship between a response variable and a set of predictors. Logistic regression analysis, unlike other regression analyses, does not require assumptions to be fulfilled regarding the distribution of independent variables. That is, assumptions such as normal distribution of predictive variables, linearity and equality of variance-covariance matrix do not have to be met. Therefore, it might be suggested that logistic regression analysis is much more flexible and it is easier to interpret the mathematical model obtained as a result of analysis by logistic regression analysis (Leech et al., 2005).

The Bernoulli Distribution

Given the binary response logistic regression based on the Bernoulli distribution, (distribution of 1s and 0s), the probability function is expressed as

$$f(y;p) = \prod_{i=1}^{n} p_i^{y_i}(1-p_i)^{1-y_i}$$

where the joint pdf is the product, Π, of each dataset being modeled is represented by the subscript i. Thus, the Bernoulli distribution for a single observation can be specified when the product term is dropped.

$$f(y;p) = p_i^{y_i}(1-p_i)^{1-y_i}$$

where y is the predicted variable being examined and p is the probability that y is equal to 1 whereas p has values ranging from 0 to 1. By inverting the order of y and p in the PDF to estimate p on the basis of y, the likelihood function can be expressed as

$$L(p_i;y_i) = p_i^{y_i}(1-p_i)^{1-y_i}$$

And this is mathematically equivalent to

$$L(p_i;y_i) = \prod_{i=1}^{n} exp\left\{y_i In\left(\frac{p_i}{1-p_i}\right) + In(1-p_i)\right\}$$

where In is the natural log (not log to the base 10 or log_{10}. By taking the log of both sides of the likelihood function to allow for summation across entire observations and to make it flexible for the algorithm used to generate the distribution parameters to converge, the Bernoulli log-likelihood function can be written as

$$L(p_i;y_i) = \sum_{i=1}^{n} \left\{y_i In\left(\frac{p_i}{1-p_i}\right) + In(1-p_i)\right\}$$

Estimation Model

In our analysis, the main goal is to specify a model which can define the relationship between dependent (predicted) variable and independent (predictive) variables in best fit with the least variable (Atasoy, 2001), that is the study sought to predict a potential customers' adoption of teller machine y based on unknown information regarding the predictive variablex_i. In general, we can write the equation for a straight line as

$$y_i = \beta_0 + \beta_i x_i + \epsilon_i$$

where $\beta_i{}'s$ are the slope coefficients, such that $x_i{}'s$ are the levels of predictive variables corresponding to the responses whose distribution we assume as $N(0,\sigma)$ as before. Furthermore, we assumed that the error term ϵ_i are independent from one another and $\beta_i's$ can be interpreted as the change in the mean response when x is increased by one unit under this model such that $y_i \,/\, x_i \sim N(\beta_0 + \beta_i x_i, \sigma)$ where $\beta_0 + \beta_i x_i$ is regarded as the system component of y. And when the predicted variable y_i is dichotomous or classified, the most eligible and economic model between the predicted variable and the predictive one or ones occurs (Seven, 1997). In measuring our predictive variables in order to estimate the predicted variable over teller machine adoption, the next issue is the choice of the functional form for our empirical model, we choose the log of the odds ratio for the adoption because it is an approximation that has been shown to dominate the commonly specified binary dependent variable. Thus, the discrete dichotomous variable is 1 for those who have adopted teller machines and 0 otherwise. The independent variable or the predictive variables are $x_1 \dots, x_n$ and the odds ratio for teller machine adoption is described as $p/(1-p)$ such that p is the probability, y_i teller machine adoption to be equal to 1. For this approach, the log of the odd ratio is the dependent variable and five predictive variables are specified below

$$y_i = log\big(p/(1-p)\big) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} \dots, + \beta_5 x_{5i} + \epsilon_i$$

where p is the probability, $\beta_0, \beta_1 \dots, \beta_5$ are the coefficients estimated from the data and the ϵ_i the variance of the random error term. The fundamental feature of this approach is that the higher the number of variables to be included in the regression equation design to explain variance of the predicted variable as shown in the above model, the less error rate in the equation will be, hence the accuracy of predictions should be high as much as possible and it is suggested to work with a reasonable number of predictive variables to lower systematic errors caused by data gathering using too many variables (Önder & Cebeci, 2001). In our model therefore, the five predictive variables denoted as x_i to predicted variable y is therefore consistent with studies concerning applied logistic regression analysis (Miller & Vannatta, 2005): Where $x_1 =$ Relative Advantage (the extent to which technology of innovation is observed as better program it replaces); $x_2 =$ complexity (how difficult technology is to comprehend and adopt); x_3 = compatibility (how consistent the technology is with the values and needs of potential adopters); x_4 = triability (degree to which the technology may be experimented with before the intention to adopt it) and x_5 = observability (extent to which the technology is able to generate visible outcomes).

3. METHODOLOGY

The Bank under Section 4 (e) of the Bank of Ghana Act, 2002 (Act 612), Section 18 1 (f) of the Banks and Specialized Deposit-Taking Institutions Act, 2016 (Act 930) and Section 99 2(b) of the Payment Systems and Services Act (2018) has provided guideline on operations of Electronic Payment Channels. This is to provide a framework for the management of an efficient and secured transmission of electronic transactions across the various payment channels especially standards on Automated Teller Machine Technology and Specification. In view of this GCB, ADB, SGSSB, ECOBANK, and NIB were selected based on their years of experience (number of years) during which they have complied with these Acts concerning automated teller machine deployment, operation, maintenance and security and have passed any regulatory monitoring exercise of the Bank of Ghana. The study employed the cluster sampling method and this involved treating each bank as a cluster - represented by the number of customers who patronized the bank's teller machines. These cluster units were assumed to be heterogeneous because of different backgrounds of customers in terms of economic classes, professions and levels of education etc. Thus, our assumption was that customers from each cluster have similar behavioral characteristic of adopting or patronizing teller machine at a given time and hence a convenience sample of 100 customers were drawn from each cluster, The predictive variables were measured using the 5-point Likert scale. It is a rating scale to measure opinions, attitudes, or behaviour and consists of a statement or a question on a single "latent" variable followed by a series of five or seven answer statements from which respondents select options that best corresponds with how they feel about the statement or question. The predicted variable on the other hand is a dummy: [Adoption equal 1 and 0 otherwise]. Using quantitative research methods, two approaches have been applied for statistical modelling of the predictive variables and our regression analysis followed the methodology set out Macmillan (1991). We first subjected the predictive variables to a principal component analysis before using the extracted components for regression analysis. It is a dimensionality reduction method that is often used to reduce the dimensionality of large data sets, by transforming a large set of variables into a smaller one that still contains most of the information in the large set. In essence, the component analysis sought to identify patterns of covariance so that trends within a comparatively large numbers of variables are summarized by a smaller number of factors (i.e., identifying pattern of common variance) in order to determine the number of components to be retained for regression analysis (Menard, 1995)

4. RESULTS AND DISCUSSION

Principal Component Analysis

Table 1: Best Fitting Stage 1: Principal Component Analysis

Construct	Cumulative %	Extracted Components	KMO Measure	Cronbach Alpha	Eigenvalues
Advantage	73.947	14	0.745	0.86	2.5514
Complexity	66.187	7	0.692	0.83	2.0697
Compatibility	65.830	7	0.718	0.87	2.3510
Triability	67.935	3	0.729	0.71	2.0380
Observability	66.956	8	0.718	0.79	2.0683

Source: Extraction Method: Principal Components Analysis 2023

Since the primary concern of the PCA is to determine the minimum number of variables that would account for maximum variance in the components, we first run PCA on the database and provide the extracted components for each construct as shown in column (iii). The retained components were then used in further analysis on the grounds that they would substantially improve prediction of the dependent variable. In the observed sample when the total variance explained by each construct were considered, the cumulative percentage for the number of components extracted under each construct was above 60%, ranging from 65% to 75%. Two further analyses can be examined: The eigenvalues or characteristic roots (symbol: λ), a numerical index that indicates the portion of the total variance among several correlated and using the eigenvalues=greater-than one rule (Kaiser, 1960), the appropriateness of our variables is confirmed in column (viii), this implied that the variables have more predictive power than any of the measured variables alone (Zwick & Velicer, 1986). The Cronbach's alpha is a technique of examining the reliability by comparing the amount of shared variance, or covariance, among the items making up an instrument to the amount of overall variance. The understanding is that, if the instrument is reliable, there must be very high covariance among the items relative to the variance. Given the very similar analysis of our Cronbach alpha reliability range, we can describe the values as good ranging from $0.7 \leq \alpha \leq 0.9$ (Hair et al. 2021).

Finally, the Kaiser-Meyer-Olkin (KMO) a measure of proportion of variance among our variables which might be common variance is estimated and KMO values greater than 0.5 indicate that our data exhibited a significant correlation ranging from 73% to 75% as shown in column (vi)

Significance of the Model

Table 2: Model Summary with ANOVA

Source	Coefficients	Source	Coefficient
Model		Regression	119.649 (5df)
R	0.906	Residuals	60.864(595df)
R-square	0.821	Total	180.503
Adjusted R-square	0.804	F	195.6648
Std Err	0.382	Sig	0.000

Predictive Variables: Relative Advantage, Complexity, Compatibility, Observability and Triability. Predicted Variable (Adoption)

Table 2 presents summary information on the significance of our model and given the explanatory power of the best fitting model, the predictive variables exhibited relatively high variation in the predicted variable, as revealed by the value of R^2 and on the average the model explained 82% of the variation in the predicted variable. This finding can be interpreted as an indicator of model-data fit. Table 3 shows the significant effect of the predictive variables on adoption with values $[F = 195.6648, \rho < 0.05]$ and the relationship described above confirm our expectation that model would be statistically significant and the trend holds for prediction.

Model Fit Statistics

Table 3: Model fit statistics

Model	Unstandardized B	Coefficient Std Err	Standardized Beta	T	Sig
Constant	0.124	0.147		0.8435	0.447
Advantage	0.265	0.049	0.579	5.4082	0.011
Complexity	0.246	0.089	0.298	2.7640	0.009
Compatibility	0.244	0.042	0.563	5.8095	0.026
Triability	0.237	0.057	0.345	4.1579	0.004
Observability	0.311	0.048	0.549	6.4792	0.012

Predictive Variables: Relative Advantage, Complexity, Compatibility, Observability and Triability. Predicted Variable (Adoption)

Given the estimated relationship in Table 3, the standardized coefficients in column 4 shows the effects on the predicted variable given the predictive variables: relative advantage, complexity compatibility, triability and observability. With reference to the standardized beta, the results show that the estimated coefficients are positive as a unit change in the predictive variables resulted in a corresponding change in the predicted variable ranging from 29.8% to 57.9%. On the basis of this regression, the fitted or predicted values of all predictive variables were statistically different from zero given their p-values in column 6. The significance relationship for complexity and triability may however be explained from the perspective of innovation process of communication channel espoused by Rogers (2003): the process in which people share important information with one another (interpersonal communication) to obtain understanding and for uncertainty reduction. Thus, this information shapes their attitude and intention after obtaining information on the functioning of the system and social reinforcement from other users, such as colleagues, friends and peers (conversation and network) whose subjective evaluation is most convincing to reduce uncertainty of individual's opinions and beliefs about the innovation and its adoption (Sherry, 1997). It is also important to acknowledge that although all the variables exhibited relatively high fitted values ranging from 0.298 to 0.579, there exists adoption gap ranging approximately from 0.421 to 0.702. If a unit change in the variables resulted in 0.579, 0.298, 0.563, 0.345, and 0.549 units increase in adoption on the average, then there exist adoption gaps. In the context of adoption performance, these distributed scores are bounded between 0 and 1, indicating the levels of adoption at any given time period given a set of predictive variables. For instance, the value of $\left(\widehat{\beta}_1 \times 100\%\right)$ is the percentage point by which actual adoption has increase given that relative advantage increases by one percentage point. Thus, if $(0.578 \times 100\%) = 57.8\%$, then this means that actual adoption is only 57.8% of the potential or the maximum capacity in terms of relative advantage, thus leaving a gap of 42.2% which can be traced back to the inherent problem within the system which are beyond customers' control. Abstracting from the distribution of these figures, it means that these are the probabilities of successes and hence on the average adoption is only 0.4668 or 47% of the maximum potential (100%) of the automated teller machines and we interpreted these figures as evidence of net benefits of system performance.

Adoption Decision

Table 4: Adoption Decision

Categories	Optional	Administrative	Total
Proportions	382	218	600
Percentage (%)	64	36	100

Source: Field Data, 2023

Table 5: Rate of Adoption

Dimensions	Innovators	Early Adopters	Early Majority	Late Majority	Laggards	Total
Proportion	131	167	213	57	32	600
Percentage(%)	21.83	27.83	35.50	9.50	5.33	100

Source: Field Data, 2023

Table 4 and 5 show distributions of cardholders over our sample in terms of adoption decision and rate of adoption. The optional innovation-decisions are choices taken upon by the clients independently of decision of other clients and whose decision may be influenced by his or her interpersonal networks, usually made more rapidly. Clearly, the decision to adopt teller machine among banks appears particularly stronger for optional category representing 382 (64%) as against administrative category representing 218 (36%). Table 5 shows the very strong behavioral responsiveness for this category of client for adoption; however, this was not the case for administrative category. Whatever the reason, it seems that this category wanted to further improve their financial circumstances and this highlights the importance of achieving a desired outcome measured in terms of economic and social factors (i.e., convenience and satisfaction). This would seem to indicate that clients who are part of the larger population are more likely to take individual decisions concerning diffusion of technology innovation and stand to gain firstly the benefit thereof. Next, a number of adopters which arise from the adoption of teller machines among the banks were identified and examined in Table 6. Similar to Table 6, our analysis complements existing literature by including novel data on adopter categories as "the classifications of members of a social system on the basis of innovativeness". The appropriateness of using the categorization was to examine innovativeness dimensions, measured in term of how different individual decided to adopts an innovation (ATM), a result which may reflect more careful social structure of clients. Comparing these results, the distribution is slightly higher for: innovators, early adopters and early majority than for late majority and laggards, a result which may not be surprising given the characteristics of these adopters (Rogers, 2003). Given the classification of adopters on the basis of innovativeness, when the individuals are similar in terms of their innovativeness (the extent to which people is relatively earlier in adopting a idea than others members of the system), the distribution appears to skew towards early majority representing 213 (35.5%) - individuals who won't act without solid proof of benefit and desirous of hearing about industry standards before taking initiative), this is followed by early adopters representing 167 (27.83%) – thus, when benefits appear visible, early adopters leap in, always looking for a strategic leap forward and are quick to decide in innovation and individual needs. Following closely are innovators representing 313 (21.83%) – who are desirous and willing to experiment with new innovation and are prepared to cope with unprofitable and unsuccessful innovation. When compared with innovators, early adopters, early majority, late majority and laggards are however skeptical about technology and its outcome and they see risk in adopting new technology or innovation. This can be observed in their distribution accounting for only 14.83% of the entire population. On the basis of Rogers (2003) further description of his categories of adopters, it was observed that early adopters of ATM (85.17%) outnumbered late adopters (14.83%) which is consistent with Rogers (2003).

5. CONCLUSION

The objective of the paper was to apply the theory of diffusion of innovation to adoption of ATM. Using the principal component analysis and regression technique, the results show that the cumulative percentages of extracted components were above 60%, ranging from 65% to 75%, the predictive variables attained the eigenvalues=greater-than one criteria and the KMO values greater than 0.5 rule were attained. The low p-values indicate significance of the explanatory variables in the estimated relationship at the 5% level. On the basis of adoption performance, the estimated probability that cardholders adopted ATM across all banks was only 0.4668 or 46.68% of the demand-sided transaction of the maximum potential of 100%, thus creating a gap of 53.42%. The distributed frequency scores for potential adopters were largely skewed in favour of early adopters (85.17%) than late adopters (14.83%). Given these distributions, it is possible to conclusion that adoption has also been heavily influenced in the context of cardholders' innovativeness. The results will serve as an important literature for banks in enriching their understanding of automated teller machines adoption given the emerging adoption gap and variations in cardholders' innovativeness. In what follows, the paper may conclude that the lower adoption score observed may be attributed to some efficiencies or "unwarranted event" which may not have driven patronage resulting in potential cardholders attempting to substitute human tellers for ATM during normal business hours. This substitutability may have huge implications for banks if adopting technology-driven strategies to ensure better customer services besides enhancing their own competitive sustainability tend to wean away. The banks should take steps to update the existing technologies relating to automated teller machine operations in order to address the challenges before enforcing any future deployment to meet end-users' expectations.

REFERENCES

Al-Emran, M & Granic, A (2020). Analysis of the Technology Acceptance Model from 2010 to 2020.

Ahmad, S., Bhatti, S.H. & Hwang, Y., (2020). 'E-service Quality and Actual Use of E-banking: Explanation through the Technology Acceptance Model', *Information Development* 36(4),503–519.

Ajzen, I (2002). Perceived Behavioral Control, Self-efficacy, Locus of Control, and the Theory of Planned Behavior, *Journal of Applied Social Psychology*. (32) 665-683.

Ajzen, I. & Fishbein, M., (1975). A Bayesian Analysis of Attribution Processes', *Psychological Bulletin* 82(2), 261–277.

Ajzen, I., (1991). The Theory of Planned Behavior', Organizational Behavior and Human Decision Processes 50(2), 179–211.

Braak, V. J (2001). Individual Characteristics Influencing Teachers Class Use of Computers. *Journal of Educational Computing Research* 25(2): 141-157

Blackwell, R. D., Engle, J. F., & Miniard, P. W. (1995). Diffusion of Innovations in Consumer Behavior. London: Dryden Press.

Davis, F.D (1986). Technology Acceptance Model for Empirically Testing New End-user Information Systems: Theory and Results: Unpublished PhD thesis, Massachusetts Institute of Technology.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User Acceptance of Computer Technology: A Comparison of two Theoretical Models. *Management Science*, 35(8), 982-1003.

Davis, F.D., (1985). A Technology Acceptance Model for Empirically Testing End-user Information Systems: Theory and Results', Doctoral dissertation, Massachusetts Institute of Technology.

Foley Curley, K. (1984). Are there any real benefits from office automation? *Business Horizons*, 27 (4), 37-42.

Fishbein, M., & Ajzen, I. (1975). Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research. Reading, MA: Addison-Wesley.

Gallini, S.M., & Moely, B.E. (2003). Service-learning and Engagement, Academic Challenge and Retention. *Michigan Journal of Community Service Learning*, 5-14.

Gefen, D., Karahanna, E and Straub, D, W. (2003). Trust and TAM in Online Shopping: An Integrated Model. *MIS Quarterly*, (27), 51-90

Gerrard, P, & Cunningham, J. B. (2003). The Diffusion of Internet Banking among Singaporean Consumers. *International Journal of Bank Marketing*, 21(1), 16-28.

Hair, J.F., Ortinau, D.J. & Harrison, D.E., (2021). Essentials of Marketing Research, McGraw-Hill, New York, NY

Horton, R. P., Buck, T., Waterson, P. E., & Clegg, C. W. (2001). Explaining Intranet Use with the Technology Acceptance Model. *Journal of Information Technology*, 16(4), 237-249.

Kaiser, H.F. (1960). The Application of Electronic Computers to Factor Analysis. Educational and Psychological Measurement, 20, 141–151

Lee, C.K., Yiu, T.W. & Cheung, S.O., (2021). Predicting Intention to use Alternative Dispute Resolution (ADR): An Empirical Test of Theory of Planned Behaviour (TPB) model', *International Journal of Construction Management* 21(1), 27–40.

Leech, N.L., Barrett, K.C. and Morgan, G.A. (2005). SPSS for Intermediate Statistics, Use and Interpretation. 2nd Edition, Lawrence Erlbaum Associates Inc., Mahwah.

Legris, J. Ingham, P. Collerette. (2003). Why do People use Information Technology? A Critical Review of the Technology Acceptance Model, *Information and Management* 40 (2003) 191-204.

Menard, S. (1995). Applied Logistic Regression Analysis. Thousand Oaks, CA: Sage

Mertler, C. A., & Vannatta, R. A. (2005). Advanced and Multivariate Statistical Methods: Practical Application and Interpretation. Glendale, CA: Pyrczak Publishing

Menard, S. (1995). Applied Logistic Regression Analysis. Sage University Paper series on Quantitative Applications in the Social Sciences, series no. 07-106. Thousand Oaks, CA: Sage.

Meimouri, N.M. Yaghoubi, M. Kazemi (2012). The Effect of Electronic Service Quality on Customers Behavioral Intentions, *International Journal of Marketing Studies*. 4 (2) 179-187.

Nguyen, V. & Nguyen, T., (2016). Perceived Risk in the E-payment Adoption via Social Network', *Journal of Economic Development* 27(12), 66–81.

Ravichandran, K. Bhargavi, S. Arun-Kumar (2010). Influence of Service Quality on Banking Customers' Behavioral Intentions, *International Journal of Economics and Finance*. 2 (4) 18-28.

Rogers, E.M. (2003). Diffusion of Innovations (5th ed.). New York: Free Press.

Sharda, R., Barr, S.H. & McDonnell, J.C. (1988). Decision Support System Effectiveness: A Review and an Empirical Test. *Management Science*, 34 (2), 139-159

Sherry, L. (1997). The Boulder Valley Internet Project: Lessons Learned. Technological Horizons in Education. *Journal*, 25(2), 68-73.

Singh, S. & Srivastava, R.K., (2020). Understanding the Intention to use Mobile Banking by existing Online Banking Customers: An Empirical Study', *Journal of Financial Services Marketing* 25(3), 86–96.

Venkatesh, V. & Davis, F.D., (1996). A Model of the Antecedents of Perceived Ease of Use: Development and Test', *Decision Sciences* 27(3), 451–481.

Venkatesh, V. & Davis, F.D., (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies', *Management Science* 46(2), 186–204.

Venkatesh, V., Morris, M.G., Davis, G.B. & Davis, F.D., (2003). 'User Acceptance of Information Technology: Toward a Unified View', *MIS Quarterly* 27(3),425–478.

Venkatesh, V. & Bala, H., (2008). Technology Acceptance Model 3 and A Research Agenda on Interventions', *Decision Sciences* 39(2), 273–315.

Venkatesh, V., Thong, J.Y. & Xu, X., (2012). Consumer Acceptance and use of Information Technology: Extending the Unified Theory of Acceptance and use of Technology', *MIS Quarterly* 36(1),157–178.

Zhang, T., Lu, C. and Kizildag, M. (2018). "Engaging Generation Y to co-Create Through Mobile Technology", *International Journal of Electronic Commerce*, Vol. 21 No. 4, pp. 489-516.

Zwick, W.R., & Velicer, W.F (1986). Comparison of Five Rules of Determining the Number of Components to Retain. *Psychological Bulletin* 99(3): 432-442