IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

The Integrating Framework For The Technology Acceptance Method Of E-Services By Numerical Acceptance

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ABSTRACT: Innovations acceptance is attracting increasing attention. Researchers are particularly interested in factors that affect the adoption of IS and IT innovations. However, despite numerous advantages of e-payment usage such as convenience, speed, efficiency and reduced cost, the economic ecosystem is skeptical to embrace e-payment systems (Adeyelure, Pretorius & Kalema, 2013)[1][2]. This research develops extended TAM model by integrating the three dimensions of trust (integrity, benevolence and competence) and two key constructs from technology acceptance models (perceived ease of use and perceived usefulness of e-payment) to explain online consumers' intentions to engage in the business relationship with e-payment. Through this framework, researchers can have a more accurate explanation of the consumer behavior and intention to accept new technology[3][4]. This framework will be used to examine consumer's behavioral intention to accept e-payment by researchers[4].

KEYWORDS: TAM, Integrity, Trust, Ability and TAM Model.

I. Introduction

Trust is one of the cardinal elements of the digital economy, and a lubricant that makes efficient markets possible. Without trust, few transactions would take place. While mutual benefit is often the reason behind a transaction, trust is the insurance or likelihood that the purchaser will receive that benefit. While trust is important for all types of business, trust is even more crucial in the online business environment. Quelch and Klein (1995) [2]showed that trust is a key factor in stimulating Internet purchases, especially at the early stages of commercial development. An identifiable stream of research therefore integrates trust with key constructs from well-known technology acceptance models, such as the TAM (Davis, Bagozzi and Warshaw, 1988) or the more recent UTAUT model (Venkatesh *et al.*, 2002). However, a more elaborate understanding of how trust and technological acceptance drive behavior may be gained when trust is decomposed into its dimensions (McKnight, Choudhury and Kacmar, 2001)[5]. We decompose trust into its three dimensions (integrity, benevolence and ability) and explore how these dimensions interact with the two key constructs of technology acceptance model to ultimately explain consumers' intentions to engage into a business relationship with the e-payment[6].

Embracing innovative technologies especially in financial services has become a major focus of research scholars in recent times (Venkatesh, Morris, Davis & Davis, 2003). Many of the studies are directed towards factors that influence user's decision to adapt innovation (Teo, Wei, & Benbasat, 2003; Venkatesh & Brown, 2001). Numerous studies have reported on how potential users' perceptions of the innovative technologies influence their acceptance or usage (Lewis, Agarwal, & Sambamurthy, 2003; Moore & Benbasat, 1991). Substantial theoretical and empirical progress has been made in explaining and predicting user acceptance of IT[7] [8]. In particular, the Technology Acceptance Model (TAM) has become well-established as a model for predicting IT acceptance, usage intentions and behavior via the mediating variables perceived usefulness and perceived ease of use (Davis 1989, Davis, Bagozzi and Warshaw, 1989). In line with a large body of research that extended the TAM (King and He, 2006; Venkatesh & al., 2003), [8]the goal of the present research is to enrich the TAM by integrating trust construct which is permissible by original TAM model.

Several techniques of e-payments are currently altering the manner businesses are carried out over the Internet, including e-banking, e-ordering and online publishing/online retailing (Okoro & Kigho, 2013), by permitting the exchange of finances and information rapidly, easily, and reliably than before. The benefits of e-payments cannot be overemphasized, ranging from cost reduction, flexibility, convenience, enhanced productivity and efficiency, tracking individual spending, and it has changed the financial ecosystem from brick and muter system to electronic payment system. However, notwithstanding its advantages, consumers in developing countries are not eager to disclose sensitive financial data over the web; the unwillingness to provide sensitive personal data for instance credit card numbers to transact businesses over the internet is still strong in developing countries (Lawrence & Tar, 2010). Despite numerous advantages of e-payment usage such as convenience, speed, efficiency and reduced cost, consumers are skeptical to embrace e-payment systems (Adeyelure, Pretorius & Kalema, 2012). This is occasioned by some vital problems such as; inability to trust the system, cybercrime, internet frauds and perceived lack of security with e-payment still discourage the escalation of e-transaction (Adeshina & Ayo, 2010). Because of lack of trust on the part of consumers, Internet transactions have witnessed stunted growth, money on an untrusted system (Akintola et al (2011). Arguably, the extant literatures have not fully addressed or further understand from user perspective why they feel skeptical about electronic payment platforms. The essence of the current study is to develop a framework that will incorporate trust in e-payment acceptance with a theoretical base from the TAM model developed by Davis, (1989)[8][9][10]. The developed model will provide confidence to e-payment patronage and also contribute to financial inclusion in the financial ecosystem.

II. Review of Literature

The Technology Acceptance Model (TAM), introduced by Davis (1986), is one of the most widely used models to explain user acceptance behavior. This model is grounded in social psychology theory in general and the Theory of Reasoned Action (TRA) in particular (Fishbein, & Azjen, 1975). TRA asserts that beliefs influence attitudes, which lead to intentions and therefore generate behavior. Correspondingly, Davis (1986, 1989) introduced the constructs in the original TAM (see Figure 1) as follows: perceived usefulness (PU), perceived ease of use (PEOU), attitude, and behavioral intention to use. Among the constructs, PU and PEOU form an end-user's beliefs on a technology and therefore predict his or her attitude toward the technology, which in turn predicts its acceptance[11].

Davis (1989) conducted numerous experiments to validate TAM by using PEOU and PU as two independent variables and system usage as the dependent variable. He found that PU was significantly correlated with both self-reported current usage and self-predicted future usage. PEOU was also significantly correlated with current usage and future usage. Overall, he found that PU had a significantly greater correlation with system usage than did PEOU. Further regression analysis suggested that PEOU might be an antecedent of PU rather than a direct determinant of system usage. That is, PEOU affects technology acceptance (TA) indirectly through PU. Figure 2 shows the validated TAM[10][12].

In the last decade, TAM has received considerable attention and empirical support (e.g., Davis, 1989; Mathieson 1991; Taylor & Todd, 1995a). We estimate that there were about 100 studies, published in journals, proceedings, or technical reports, related to TAM between 1989 and 2001. In these studies, TAM was extensively tested using different sample sizes and user groups within or across organizations, analyzed with different statistical tools, and compared with competing models (Gefen, 2000). It was applied to many different end-user technologies such as email (Adams, Nelson & Todd, 1992; Davis, 1989), word processors (Adams, Nelson & Todd, 1992; Davis, Bagozzi & Warshaw, 1989), groupware (Taylor & Todd, 1995b), spreadsheets (Agarwal, Sambamurthy & Stair, 2000; Mathieson, 1991), and World Wide Web (Lederer, Maupin, Sena & Zhuang, 2000). Some studies also extended TAM by including additional predictors such as gender, culture, experience, and self-efficacy. Overall, researchers tend to suggest that TAM is valid, parsimonious, and robust (Venkatesh & Davis, 2000)[13][14][15].

Davis (1989) developed and validated the scales for PEOU and PU and found six highly reliable items for each construct with a Cronbach's alpha of .98 for PU and .94 for PEOU respectively. In succeeding studies, the measurement items for these constructs varied from researcher to researcher (Adams, Nelson & Todd, 1992)[10][12][13][14]. As a result, the cumulative number of items for measuring PU has increased from the original six to currently about 50, and that for PEOU has increased from six to 38. Appendix shows nine different instruments for PU and PEOU employed in the existing studies1 [15]. Upon closer scrutiny of the list, we found that the differences in measurement items between studies tend to be the result of adapting TAM to different technologies. The essential definitions of the constructs to be measured are still the same. Therefore, we conclude that the empirical findings on the relationships between the constructs in TAM are not affected much by how the constructs are measured[16].

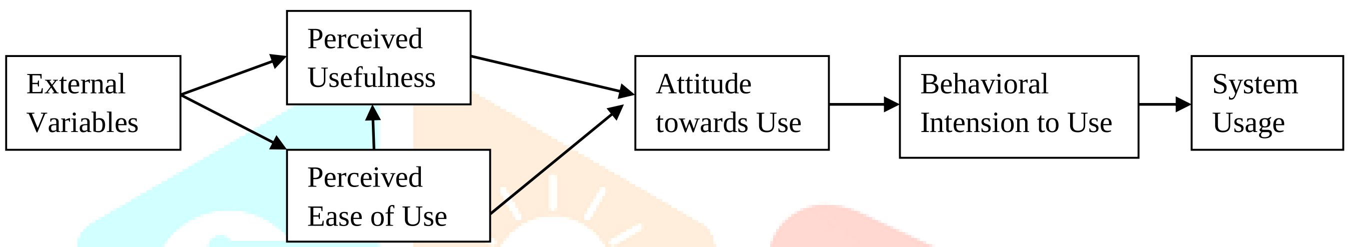

Figure 1: The Original Technology Acceptable Model.

Figure 2: A Validated Technology Acceptable Model.

III. Research Methodology

Meta-analysis is defined as the "statistical analysis of a collection of analysis results from individual studies for the purpose of integrating the findings" (DerSimonian & Laird, 1986). An individual test typically provides summary statistics that indicate the significance of the test results. In meta-analysis, we need to convert the statistics into a common metric called effect size, which is usually in the form of the Pearson Product Moment Correlation. Essentially, an effect size represents the degree to which the phenomenon is present in the population (Cohen, 1977). In this section, we explain how we select individual studies for our meta-analysis and how we estimate the effect size for each sample study[17].

One of the important assumptions in meta-analysis is the independence of individual findings; effect sizes such as correlations in different studies are statistically independent. This assumption is frequently violated because some studies often report more than one correlation or effect size based on the same sample (Martinussen & Bjjornstad, 1999)[18]. To observe this assumption, when we selected studies and calculated the effect sizes, we carefully checked the sample to make sure they were not based on the same data. If multiple tests based on the same sample were conducted, we selected only one of them and recorded its statistics[17][18][19].

Initially we found a total of 91 empirical studies. Among them, 65 studies did not report correlation coefficients or other statistics that we could convert into correlation coefficients. Thus, we dropped those studies and selected the remaining ones. Among the 26 selected studies, seven of them are working papers or published in conference proceedings. Since some studies reported test results based on multiple samples (e.g., Davis, 1989; Subramanian, 1994), we obtained 102 correlation coefficients in total from the 26 selected studies.

In this study, the Pearson Product Moment Correlation is used as the index of effect size to represent the empirical strength of a relationship between each pair of the constructs in TAM. We selected the statistic because of its ease of interpretation and the availability of formulae for converting other test statistics into correlation coefficients (Lipsey & Wilson, 2000). In addition to effect size, we also encoded the sample size for each study and whether an effect size is positive and statistically significant. For each pair of the constructs in TAM: PU, PEOU, and TA, we calculated the effect sizes as follows:[17][18][19]an effect size is simply a correlation coefficient, if it was reported; otherwise, it is obtained through a conversion by using a formula. For example, if a t-value is reported, we converted it into a correlation using the formula is as follows:

$\boldsymbol{r} = \sqrt{\frac{\boldsymbol{t^2}}{\boldsymbol{t^2+df}}}$where df is the degree of freedom. Wolf (1986) provides guidelines for converting the most common test statistics to r. Cohen (1965, 1977), Friedman (1968), Glass, McGaw ans Smith (1981), and Rosenthal (1984) discuss the conversion process and provide guidelines for transforming some less common statistics. This procedure is widely used in many other studies (e.g., Szymanski & Henard, 2001).

IV Data Analysis

In this section, we analyze the data and report findings in two steps. First, we describe the correlations in terms of range, direction, statistical significance, and sample size. These data will reflect the nature and diversity of the existing findings on TAM. Second, we present the findings from the univariate analysis of the correlations. The purpose here is to show the central tendencies of the existing findings and their statistical significance[16][17].

V Descriptive Statistics

Based on the 26 selected studies, we obtained 102 correlations as summarized in Table 1. Note that not all studies reported all the three correlations or equivalents. Among the 102 correlations, 37 PU-TA correlations were obtained from 21 studies, 32 PEOU-TA correlations from 20 studies, and 33 PEOU-PU correlations from 21 studies. The number of studies for each of the three relationships is approximately the same. According to the range of correlation coefficients, it is easy to see that the strength of each relationship varies greatly from insignificant to strongly significant. For instance, the correlation between PEOU and PU changes from 0.003 to 0.92. In addition, the correlation coefficient between PU and TA were insignificant in some instances, although most studies found otherwise[15][16].

As expected, most studies reported positive significant findings and few nonsignificant or negative ones. According to Table 1, the percentage of positive significant correlations of PEOU-PU is the highest among the three relationships, while PEOU-TA has the highest percentage of positive non-significant correlation. The sample size varies from study to study. In some studies, the sample size is as low as 36; while in others, it is as high as 1370. Of course, the extreme cases are few in number. The average sample size indicates that the number of subjects used in the selected studies is very close across all three relationships.

Link	#of Studies	# of Correlations	Range of Correlation Coefficients		Positive Significant Correlations		Positive Insignificant Correlations		Range of Sample Sizes			Cumulative Sample size
			From	To	#	%	#	%	From	To	Average	
PU-TA	22	36	.08	0.98	22	62.23	3	5.4	37	1371	180	6055
PEOU-TA	21	33	0.06	.58	18	54.0	11	38	36	1371	195	5745
PEOU-PU		22	34	0.004	0.91	22	64.4	7	18.3	40	1371	5422

Table 1: Summary of Selected Correlations

Link	Sample-Size Adjusted Correlation	Simple Mean Correlation	Correlation from Z	Sample Variance	Fail Safe $N_{0.05}$	Confidence Interval
PU-TA	0.4223	0.59	0.67	0.02334	132	(0.40,0.67)
PEOU-TA	0.3769	0.38	0.38	0.0375	-0.5	(0.22,0.34)
PEOU-TA	0.5679	0.60	0.67	0.2564	73	(0.40,0.69)

Table 2: Means and Variance of Correlations

Here $r = \frac{\sum N_i r_i}{\sum N_i} whrerN_i, r_i$ are the sample size and the effect size of test i, respectively. To use the Fisher r to Z transformation, three steps are followed (Wolf 1986). First, each correlation is transformed into Fisher's Z score using the for $Z = 0.5 * Ln[\frac{1+r}{1-r}]$ where r is an individual correlation coefficient. Next, we compute the sample size weighted average of the individual Z scores for each pair of the constructs in TAM. Finally, we convert the weighted average Z score back into a correlation coefficient.

There are some discussions regarding these methods. Some suggest the necessity of using the Fisher r to Z transformation in meta-analysis, while others feel there is not much difference between simple mean and the Fisher r to Z transformation (Wolf, 1986). Schmidt, GastRosenberg and Hunter (1980) discussed the issue and reported a study based the Fisher transformation. In the current study, we employed both techniques[19][20].

It is also commonly believed that correlations estimated from larger samples and more reliable data sources can produce a mean correlation closer to the population mean, all else being equal (Hunter & Schmidt, 1990; Szymanki & Henard, 2001). Thus, it is desirable to calculate reliabilityadjusted mean. However, we found that it is difficult to do so due to the fact that many source studies failed to report reliability data. Therefore, in the current paper, we chose sample-size-weighted mean instead of reliability-adjusted mean. Szymanki and Henard (2001) did the same in their recent meta-analysis on customer satisfaction.

Fisher r to Z transformation consistently results in larger means than the other two methods. This inflation phenomenon has been reported previously (Hunter, Schmidt & Jackson, 1982; Schmidt, Gast-Rosenberg & Hunter, 1980). Second, we found that the mean effect sizes obtained using the Fisher r to Z transformation and simple average are almost identical, while the results from the sample-size-adjusted method are smaller. We rechecked sample sizes and re-calculated the means, and found that some extreme sample sizes have an apparent effect on the means. For example, the correlations for a study with a sample size of 1,370 are all relatively small (between 0.31 and 0.37)[19][20].. When it is removed from the meta-analysis, the averages become larger and comparable with those obtained from the other two methods. It indicates that the sample size adjusted method may not be appropriate for the current study. Thus, we will interpret the results of this study based on the Fisher r to Z transformation method[21][22].

According to Cohen (1977), the magnitude of an effect size is small when it is close to 0.10, medium when it is close to 0.30, and large when it is close to 0.50. By this rough guideline, our meta-analysis suggests a medium-sized effect for the relationship between PEOU and TA, and large effect sizes for PU-TA and PEOUPU. Also, note that the effect sizes for PU-TA and PEOU-PU are almost identical to each other. It is different from the general perception; our study does not suggest that the PU-TA relationship is stronger than the PEOU-PU relationship[22].

To show the statistical significance of the mean effects, we computed the 99% confidence intervals for each mean estimate, based on the assumption that individual correlations are normally distributed. These intervals portray the range of effects that might exist in the true population given the presence of errors and variation in the calculation of sample effects. According to the results in Table 2, no interval contains zero, which therefore suggests that all three mean effects are significantly different from zero.

To further test the significance of the findings, given the possibility that we may miss the studies that report null effects (r = 0), we calculated the fail-safe N for p = 0.05 using the formula $N_{f0.05} = \left[\frac{\sum Z}{1.645}\right]^2 - N$, $where \sum Z$ is the sum of individual Z scores and N is the number of tests. A fail-safe N represents the number of additional studies confirming the null hypothesis (r = 0) that would be needed to reverse a conclusion that a significant relationship exists (Cooper, 1979). Table 2 shows that the mean correlations for PEOU-PU and PU-TA are significantly different from zero, to the extent that 71-131 of null effects would have to exist to bring the respective mean estimates down to a level not considered statistically significant. However, the mean correlation for PEOU-TA does not pass the fail-safe test as indicated by the negative $N_{f0.05}$.

As we pointed out before in this study, we selected the individual correlations reported for the model rather than the average of the correlations reported within a study. The former is often referred to as individual-level analysis, while the latter is considered study-level analysis. Hunter and Schmidt (1990) raised the possibility that an individual-level analysis might underestimate the sampling-error variance and the generalizability of the estimates. To address this concern, we computed the variance due to sampling error and standard deviation for each relationship. The results show that the variances of sampling-error are very close to each other, and therefore suggest that an individual level analysis is appropriate within the context of this meta-analysis.

VI CONCLUSION

This meta-analysis was designed to synthesize and analyze the existing empirical findings on the Technology Acceptance Model (TAM). It examined the relationships in TAM with a larger sample size, which is impossible to achieve in a traditional empirical study. The results of our study in general confirm Davis' original findings: Among the three constructs in TAM, both the relationships between PEOU and PU, and between PU and TA are strong, while the relationship between PEOU and TA is weak. Here we measured the strengths of the relationship from three perspectives. First, with respect to the magnitude of a mean effect, we found the mean effects for PEOU-PU and PUTA are large, while that for PEOU-TA is medium. Second, with respect to the statistical significance of a mean effect, we found that all three mean effects are significantly positive at the level $\alpha = 0.01$. Finally, with respect to the fail-safe test significance, we found that between 71- 131 null effects would have to be hidden away in file drawers for the mean correlations between PEOU and PU, and between PU and TA to be non-significant, which seems unlikely. However, the mean effect for PEOU and TA does not pass the fail-safe test, in the sense that one additional study reporting a null effect would lead to the effect being non-significant.

Of course, when interpreting or applying the results of this research, some caution is advised. As with any other research methodology, meta-analysis has its assumptions and limitations. One of the major difficulties to applying meta-analysis to the studies on TAM is that the findings of many previous researchers are generated by multivariate analyses such as multiple regressions, factor analysis, and structural equation modeling. Meta-analysts have not yet developed effect size statistics that adequately represent this form of research findings (Lipsey & Wilson, 2000). Consequently, many sample studies were dropped from our list. Otherwise, the results of this study would be more accurate.

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