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Citizen Adoption in E-Government Systems:
A Meta Analysis

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ABSTRACT

Electronic government (e-government) refers to a system of information, communication, and interaction between government and its citizens. E-government adoption has been studied for more than a decade with several meta-analytic studies being produced in that time. This study is differentiated from prior meta-analyses as it splits the empirical studies into pre-adoption and post-adoption studies to allow a clearer model of e-government. The authors found different determinants and distinct models for pre- and post-adoption of e-government. In the two models (pre-adoption and post-adoption), trust is only related to pre-adoption studies. Originally, 98 studies were coded, but with the focus on pre-adoption and post-adoption, 53 were used in the final models as they contained the attributes of interest.

KEYWORDS

Citizen Participation, Electronic Government, Models, Post-Adoption, Pre-Adoption

1. INTRODUCTION

Adoption is a behavioral process that occurs over time. Karahanna, Straub, and Chervany (1999) discuss the two stages of the adoption process, including the pre-adoption stage, which is the stage before the system's initial use, in our case, the e-Government system. The second stage is the post-adoption stage, which is the stage after the technology is implemented. This post-adoption stage is when the users include the e-Government technology in their routines. The adoption of e-Government systems has been of global importance in recent years (Kumar et al., 2021; Moreno-Enguix et al., 2019).

In the e-Government context, we propose that studies used in meta-analytic studies should consist only of those in a single adoption stage. Therefore, the pre-adoption stage and the post-adoption stage studies should be assessed separately. During analysis, the studies should be separated because of differences in behavior in each stage by citizens using e-Government systems. The pre-adoption phase involves the initial intention to use the technology and not use. In contrast, the post-adoption phase is when the system is being used. During use, citizens form actual use routines during the post-adoption phase. Because there are behavioral differences between the two phases, we propose that each of these models' determinants be distinct (Karahanna et al., 1999). This paper identified

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significant differences between determinants of pre-adoption and post-adoption of e-Government systems using a meta-analysis. In contrast, prior studies combined the pre-adoption and post-adoption studies when examining e-Government, attempting to provide a meta-analysis of studies investigating two distinct behaviors.

Two key factors motivate this research. First, in prior studies, the two stages of adoption (pre-adoption and post-adoption) had been examined together in a meta-analysis (Rana et al., 2011; Rana et al., 2012). Typically, the studies used well-established theories using model measures that are invariant over different conditions (Kang et al., 2017); such as the Technology Acceptance Model (TAM), Diffusion of Innovation theory (DOI), DeLone and McLean IS success model, Unified theory of acceptance and use of technology (UTAUT), and theory of planned behavior (TPB). TAM has been the most studied model (Rana et al., 2015b), with many of its constructs used in other models. When the meta-analytic approach combines both pre- and post-adoption studies, the analysis provides inconsistent determinants of both stage behaviors. For example, while perceived usefulness and perceived ease are significant in pre-adoption studies (e.g., Alomari, Woods, and Sandu, 2012 and Lu, Huang, and Lo, 2010), they are weaker in post-adoption studies (Almahamid et al., 2010). The technology acceptance model (TAM) is related to the pre-adoption stage, providing explanatory power for the intention to adopt a system through the variable of behavioral intention to use. Also, trust is demonstrated as an important antecedent that is present in pre-adoption but not in post-adoption studies. Actual use can only be present in post-adoption studies.

The second motivation is the increasing importance of e-Government systems, mainly as many governments have already implemented some systems and seek to implement more in coming years. It is important to understand the implication of e-Government systems for governments globally. Our meta-analysis includes a studies from developed (26% of data) and developing nations (74% of data) and shows the global trends in adoption and the importance of the shift to post-adoption studies with no clear difference in results based on national development levels. Further, there are significant benefits from e-Government adoption (European Commission, 2019) that continue to drive the adoption of these systems as a global phenomenon. For instance, e-Government strategy has been a big positive influence on smart-city infrastructure projects (Maestre-Gongora & Bernal, 2019). Therefore, improved adoption measures will enhance future smart-city developments. The importance of the role of government in their ability to influence public opinion, as shown by Gao et al. (2019), also suggests a proactive role for government to influence system adoption. The broader government's focus on IT can also influence local adoption of e-commerce solutions, suggesting benefits for governments that proactively approach these solutions (Ahluwalia & Merhi, 2020). The benefits can also flow through to enhancing productivity and efficiency of public asset management (Moreno-Enguix et al., 2019). As the literature now increasingly includes post-adoption studies, the connection between intended and actual behaviors is important to guide future e-Government system initiatives.

Based on these motivations, it is necessary to distinguish between pre-adoption and post-adoption studies. Pre-adoption studies are numerous and concentrate on the intention to use and relevant factors such as citizen e-participation levels (Ifinedo et al., 2021); in contrast, the post-adoption process has not been heavily studied, and the intention to continue use of the system is formed. By splitting the studies into pre-adoption and post-adoption, we can examine each of these distinct intentions. Investigating and finding the determinants of continued use is important for practice as enhances our understanding of what is essential for use and continued use, which informs governments to implement cost-efficient services through their e-Government initiatives (e.g., Moreno-Enguix et al., 2020). While research continues to study pre-adoption, post-adoption and the intention to continue using the e-Government system, will not get the focus it deserves. There is a difference between adopting an e-Government system and the decision to continue using it. Taking this approach in the study of e-Government will enable the field to match what is occurring elsewhere as research on other types of information technology is now emphasizing the split between pre-adoption and post-adoption (Gupta et al., 2020).

Bhattacherjee (2001) argues there are substantive differences between initial acceptance or first-time use (pre-adoption) and continuance behavior (post-adoption). So the successful use of an e-Government system should rely on the initial acceptance (pre-adoption) and the continued use (post-adoption). In a similar way, the study of mobile government (m-Government) systems is nascent and so pre-adoption studies such as Talukder et al. (2020) are appropriate. Since the acceptance and continued use of the systems are separate decisions, we should examine separately the underlying data in each area. The reasoning for this is pre-adoption looks at the initial intention to adopt a technology (Venkatesh et al., 2001), versus post-adoption looks at the antecedents for continuous use. Bhattacherjee (2001, p. 351) underscores this point by stating that "the long-term viability of an IS and eventual success depend on its continued use rather than first-time use." In post-adoption, the actual performance of a system may exceed the initial expectations and will engender continued use (Gupta et al., 2020), or in their final confirmation, they may decide to discontinue using the technology (Bhattacherjee, 2001). Since pre-adoption expectations shape post-adoption perceptions, it is crucial to split these very different concepts. However, the initial adoption behavior does not necessarily lead to continuous use, as the continuous antecedents are different; therefore, by treating each phase as separate we can advance work on problems such as low levels of e-Government services use.

In summary, the current literature that studies the pre-adoption and post-adoption stages together cannot provide a comprehensive picture of each stage of pre- and post-adoption. Rana et al. (2012) and Rana et al. (2011) used meta-analysis to investigate 70 papers in e-Government adoption. However, they included papers from pre-adoption and post-adoption and did not distinguish between these two behavior stages. Several papers contained studies that included both pre-adoption and post-adoption stages in the same e-Government study. Rana et al. (2012) also investigated the types of e-Government applications used and whether issues relating to optional/mandatory have caused a difference and examined the impact on the country's economic development.

The meta-analysis concept enables weighted analysis on citizens' intentions pre-adoption and post-adoption to use e-Government services. In addition, meta-analysis allows us to synthesize many empirical articles to study the association between these variables cumulatively. Our meta-analytic study covers research published from 2002 to February 2017. Structured Equation Modeling (SEM) is used on the meta-analysis correlation data in the MPlus software as MASEM (meta-analysis structured equation modeling) to check the new models' fit. Thus, the use of SEM analysis after meta-analysis provides us with opportunities, but as the MASEM literature cautions, we have exercised care when drawing inferences from the results (Landis, 2013).

The present study provides insights into the fundamental research question: What are the determinants of pre-adoption and post-adoption of citizens' use of e-Government services?

We structure the rest of the article as follows. We first provide an overview of past studies on e-Government adoption and develop the hypotheses. We then summarize the meta-analytic method employed and the key results. Finally, we conclude and demonstrate the contribution of this study.

2. METHOD

A meta-analysis approach (Hunter and Schmidt, 2004) was adopted to test the proposed hypotheses. A meta-analysis is a quantitative approach that aggregates findings and effect sizes across individual studies. The meta-analysis's advantage is reconciling conflicting results among the research findings to study the strength of the underlying relations and causalities. While the approach is more common in the sciences, it is increasingly important in the social sciences to understand human behaviors. For example, Chang and Huang (2020) used the approach to investigate the different contexts in which people seek health information and what influences their search. In addition, Yu et al. (2020) investigated privacy concerns and risks, showing that the perception of a privacy risk reduces information disclosure intentions but not the actual information disclosure behaviors.

Our meta-analysis is based on the review of empirical studies related to citizens' pre-adoption and post-adoption of e-Government systems. In this study, effect sizes are described as correlation coefficients. Importantly, meta-analysis enables researchers to discern whether relationships exist and provides overall estimates regarding the magnitude and direction of those relationships. We followed the meta-analysis process outlined by Hunter and Schmidt (2004) to aggregate and analyze correlations reported by prior research and draw valid conclusions. The meta-analysis process has been used to identify studies, code studies, analyze data, and report data.

2.1 Identifying Studies

We performed a search of ProQuest to identify e-Government studies from a citizen adoption perspective. Prior studies have included the tax officers, tax departments, and companies. We excluded these studies and focused on e-Government systems where citizens are the users. We searched for research articles, conference proceedings and theses in February 2017, using search terms including e-govt, e-citizen, e-administration, electronic Government, e-tax, g2c e-Government, e-voting, tax e-filing, online tax, e-service, and e-governance. We located 712 articles and downloaded them into a word document. Scanning these files, we removed those that did not contain empirical work or did not study e-Government for citizens. After the process, we were left with 123 articles to code in our coding spreadsheet.

2.2 Coding Studies and Paper Pre-Selection

The articles were coded and given a code line number, independent variable, dependent variable, citation, study part, number of participants, study r, $r_{(cme)}$, which is the correlation between the independent (y) and dependent variable (x), direction, r_{xx} (which is the reliability estimate for x), r_{yy} (which is the reliability estimate for y). As well as these variables, additional items on each e-Government study were coded, such as type of e-Government system, country, post or pre-adoption, the gender of study participants, whether the system was optional or mandatory, and level of use. Some data coded were not subsequently used, but as much data as possible was collected and coded in the process. In total we did not enter data for 25 papers as we found it not possible to code their data for the following reasons. Thirteen did not contain sufficient effect size data. Three items were duplicates, such as a Ph.D. thesis containing two studies and two articles that published the studies from the thesis. We combined two articles as they were from the same author and related to the same study; one article contained a correlation matrix only, and the other article contained Cronbach's alpha information and our analysis required the combined information. Finally, we matched our sample to the articles coded by Rana et al. (2015b), noting our data collection period ended in February 2017, which included articles not in the Rana sample (Appendix A). We also did not code several studies that Rana coded because we classified articles as pre-adoption and post-adoption. Four studies containing both pre-adoption and post-adoption in the same study were dropped. There were three studies not included as they used factors different to those used in the rest of the sample and so we could not synthesize them with models of interest. We dropped two articles as they related to e-Government systems that served the Government or companies rather than citizens. Overall, 98 studies were coded.

The level of use of the e-Government system was noted, such as gathering information, communication, or interaction. However, some of the information we endeavored to collect in our coding spreadsheet from the underlying studies could not be collected as not every study included the data; for instance, not all studies divided the sample by gender and so we could not determine the number of female participants.

The effect sizes were presented differently between studies and needed to be converted to r to be coded in the meta-analysis. For example, we used established formulae to convert data to r where studies presented data in log odds ratios(Hunter & Schmidt, 2004) or Kendall's Tau (Walker, 2003).

The process to check the data occurred once one author had coded the data and all other authors reviewed the coding. Finally, one author went through and reviewed all the papers and noted where the data was taken from in the paper, and reviewed any comments made by checking the comments from other authors. There were 20 papers where we discussed the items with a meta-analysis expert. The expert reviewed the coding and advised how they believed the item should be coded. We prepared a separate spreadsheet listing the papers coded and where each of the data items was located (highlighted in each paper) to aid this process. This spreadsheet listing was beneficial in the review and checking of the coding back to the underlying study.

2.3 Variable Coding

Many empirical studies coded in this meta-analysis were based on TAM, and the attributes and constructs used to form it have been substantiated. The constructs have been widely validated survey instruments, and the measures have very high Cronbach's alphas. In TAM, the items such as perceived usefulness and ease of use have standard definitions. For example, perceived usefulness is the degree to which an individual believes that using a specific system would enhance their job performance (Davis, 1989). This means that studies using these surveys and constructs mean the same thing in each study. We have discussed the attribute of trust below.

In the meta-analysis presented by Rana et al. (2015b) each pair in the meta-analysis was examined to generate a cumulative construct diagram shown in Appendix B. The meta-analysis in Rana et al. (2015b) included all the studies based on multiple models – TAM, DOI, IS success model, TPB, and UTAUT. The diagram is extensive and challenging to understand. They then measured the weights of relationships by counting the number of times a relationship was significant over the total number of relationships. They relied on an approach adapted from Jeyaraj et al. (2006) to do this weighting process. We show the weights in Appendix C.

Given the weighted table of attributes in Appendix C, Rana et al. (2015b) reduced the diagram from Appendix B down to the diagram shown in Appendix D. Appendix D shows an e-Government adoption model including the most frequently used relationships and weights shown in Appendix C. We use the eight most frequently used relationships from Rana et al. (2015) table on relationships shown in Appendix C. The most frequently used items are shown below in Table 1. These items are *actual use, intention to use/behavioral intention, perceived usefulness, perceived ease of use, attitude*, and *trust*. The most frequently used items also corresponded with TAM. We relied on the 2003 article by Gefen et al. (2003), which incorporated the factor *trust* into the TAM model. We show in Table 1 the number of pairs used in deriving the information in the Rana et al. (2015b) study compared to the number we have used in this study. The studies are different because of distinct data collection periods, whether citizens are the e-Government system users, and ensuring the studies are pre-adoption or post-adoption. We compared all the papers we included to those in Rana et al. (2015b), and Appendix A shows the sample of papers in each study and which match and which are distinct.

We examined the underlying papers related to these relationships and noted an interesting aspect of the *trust*-to-*behavioral intention* relationship. The *trust* factor used in the underlying papers that made up the Rana et al. (2015b) studies include several distinct types of trust, including trust in the Government, trust in the Internet, trust in the e-Government website, and general trust. Theoretically, the concept of trust being considered in the underlying papers studying pre-adoption can be considered as two distinct forms. First, trust in the Government, which involves confidence in the Government. Second, trust in the Internet, covering data security and privacy of a citizen's data, enabling technologies significant to the citizen's intention to adopt the system; discussed in the pre-adoption papers as early trust or initial trust. As a result, we decided only to use the factor *trust* in our initial meta-analysis model. We initially discarded the factors trust in the Government, trust in the Internet, and trust in the e-Government website. Therefore, when considering the relationship of *trust* to *behavioral intention* (Table 1), the studies used in Rana et al. (2015b) represent 22 pairs, of which we used 10 pairs. As we carefully analyzed the underlying papers to distinguish between the distinct forms of trust, we included fewer pairs relating to than the Rana et al. (2015b) study. We investigated this further in the SEM section and created SEM Model 1 using this restricted or

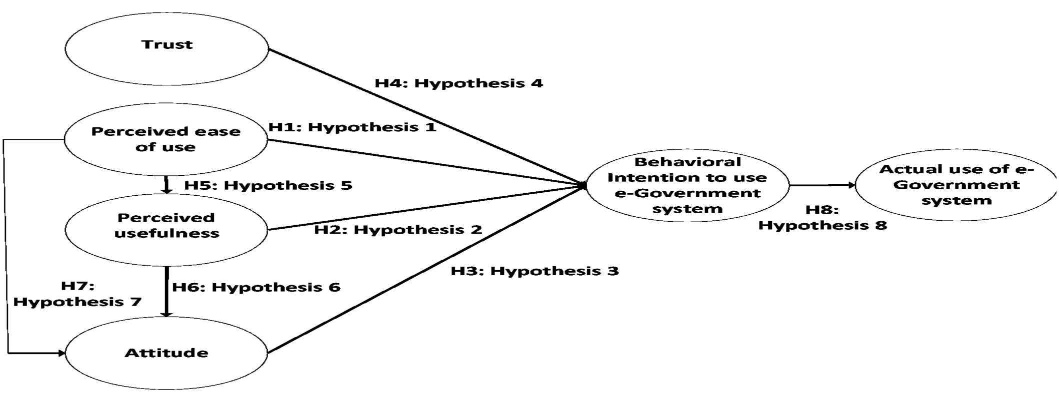
Table 1. Most frequently used relationships comparing Rana et al. (2015b) to this study

Independent variable	Dependent variable	Number from Rana study, different time period, not just citizens, and pre- and post-adoption	Number used in this study, up until 2017, focusing on citizens, and splitting pre- from post-adoption
Perceived ease of use	Behavioral intention	27	42
Perceived usefulness	Behavioral intention	24	44
Perceived ease of use	Perceived usefulness	20	31
Trust	Behavioral intention	22	10
Attitude	Behavioral intention	16	17
Perceived usefulness	Attitude	14	17
Perceived ease of use	Attitude	13	12
Behavioral intention	Actual use	10	8

narrow definition of trust. Then we created SEM Model 4 that included the broad definition of trust that combines trust in the Government, trust in the Internet, trust in the e-Government website, and trust. The two models enabled us to assess whether these different types of trust caused a significant difference in the model's fit.

In Figure 1, we show the research model for pre-adoption. We have based the model on the relationships on the relationships for TAM.

Figure 1. Research Model for pre-adoption



The model is very close to the Technology Adoption Model (TAM). It incorporates the inclusion of the factor trust into the TAM model, following Gefen et al. (2003). Therefore, we begin by unpacking the research model by discussing the hypothesized relationships between critical factors in the research model.

Hypothesis 1: *Perceived ease of use* has a positive influence on *behavioral intention to use* the e-Government system.
Hypothesis 2: *Perceived usefulness* has a positive influence on *behavioral intention to use the e-Government system.*
Hypothesis 3: *Attitude* has a positive influence on *behavioral intention to use the e-Government system.*
Hypothesis 4: *Trust* has a positive influence on *behavioral intention to use the e-Government system.*
Hypothesis 5: *Perceived ease of use* has a positive influence on *perceived usefulness*.
Hypothesis 6: *Perceived usefulness* has a positive influence on *attitude*.
Hypothesis 7: *Perceived ease of use* has a positive influence on *attitude*.
Hypothesis 8: *Behavioral intention to use the e-Government system* has a positive influence on the *actual use of the e-Government system*.

We include in Hypothesis 8 on the intention to actual use as three studies have included these attributes in their study. However, in pre-adoption, we do not expect to see actual use.

In Figure 2, we show the research model for post-adoption. This is the same model used for pre-adoption (Figure); however, we removed the *trust* factor along with H4, as *trust* is not present in the underlying post-adoption papers used in the meta-analysis. *Trust* as a pre-adoption factor was initially not evident until we split the data between pre-adoption and post-adoption. The reason for not being in the meta-analysis for post-adoption is that the underlying studies coded for post-adoption in this meta-analysis study have no *trust* factor in their underlying models. Therefore, we did not include the variable *trust* in the post-adoption model for the meta-analysis and this is a key distinction between the two adoption models. Reviewing the underlying papers coded for post-adoption, we found that *trust* was considered in many papers, discussed in a few papers, but was not included in any of the empirical models.

Therefore, for the meta-analysis, there are three research models. The first research model relates to the pre-adoption model shown in Figure 1. The second model relates to the post-adoption model shown in Figure 2. Finally, the data from model 1 pre-adoption and model 2 post-adoption are combined. This research model is the same as Figure 1, which is the research model for pre-adoption, as trust is included.

We used the articles in Appendix E in the analysis as they contained the research model attributes. Therefore, we originally coded 98 studies. However, when we analyzed these papers and focused on our research models, we eventually coded only 53 of the 98 studies as they contained the items in the research models we were focusing on (Appendix E).

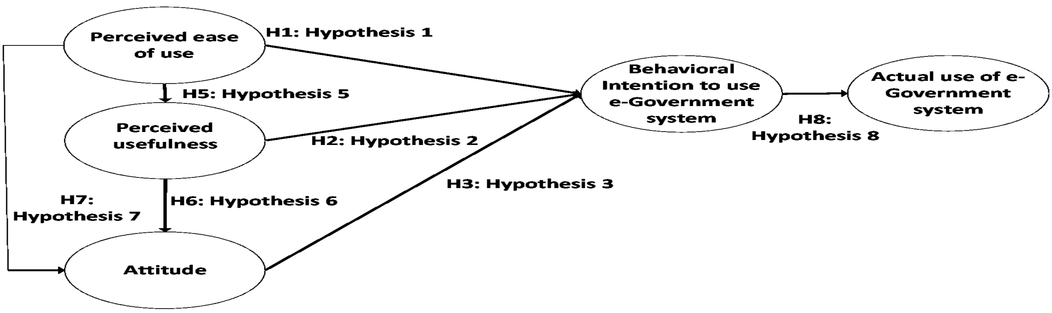
3. ANALYSIS

In this study, we first performed a meta-analysis using our research models of pre-adoption, post-adoption, and both. Then we performed an SEM analysis using the correlation coefficients from the meta-analysis.

3.1 Meta-Analysis

We used the Hunter and Schmidt (2004) method of calculating statistically corrected effect size estimates. This study measured an estimate of the population correlation *p* by using Pearson's correlation coefficient, *r.* In addition, we performed the weighted mean effect size ($\check{r}$) to correct for sampling error, which $\check{r}$ considers each study's sample size and thus creates a weighted average of correlations. Based on Hunter and Schmidt (2004), the estimate of the population correlation is given by $\check{r}$ = å$N_i r_i$ / åN_i, where N_i is the sample size of each study and r_i is the observed correlation value of each study. We calculated all estimates using Comprehensive Meta-analysis software (Bornstein et al. 2005).

Figure 2. Research Model for post-adoption



For each study, we obtained the following information: the sample size, the reliability of constructs (as reported using Cronbach's alpha or, if not available, the reported composite reliability or internal consistency scores), and correlation coefficients for each pair of the relationship. For studies that did not provide average reliability, we used a conservative standard of 0.80 (Bommer et al., 1995). Several studies used logistic regression to calculate the odds ratios as the effect size estimates. We converted these effect size estimates into Pearson's r to facilitate interpretation (see Borenstein et al., 2009). By using these values, the figures are normalized and fall between -1 and +1. Finally, we reported the mean correlation coefficients for each bivariate relationship. We constructed confidence intervals around the weighted mean correlation coefficients to facilitate hypothesis testing.

We corrected for measurement errors because of unreliability in measurement (Hunter and Schmidt, 2004). We calculated the correlation between the variables to correct for measurement error. According to Hunter and Schmidt (2004), the estimate of the true score correlation is given by: $r_c = r_{xy}/(\ddot{O}r_{xx})(\ddot{O}r_{yy})$, where r_c is the effect size corrected for measurement error, r_{xy} is the reported correlation between the variables, r_{xx} is the reliability estimate for the independent variable and r_{yy} is the reliability estimate for the dependent variable.

3.2 MASEM Model

Our second goal after performing the meta-analysis (synthesizing the key relationships) was to test our proposed structural models to understand the path structure between the variables of interest. We used three models, with Figure 1 focusing on pre-adoption, Figure 2 on post-adoption and Figure 1 on both pre-adoption and post-adoption. To do so, we used our meta-analysis results from Table 2 using meta-analytic techniques (MA) with structural equation modeling (SEM) to test for structural paths using the technique of MASEM. The resulting models are SEM Model 1 and SEM Model 4, which are both pre-adoption models, with SEM Model 1 having a narrow definition of trust and SEM Model 4 having a broad definition of trust (trust of the Internet and trust of government). SEM Model 2 and SEM Model 5, which are post-adoption models. SEM Model 3 and SEM Model 6 relate to the combined pre-adoption and post-adoption model, with SEM Model 3 having a restricted definition of trust and SEM Model 6 including all trust factors.

To evaluate model fit for the SEM, we use fit criteria from structural equation modeling. We used the root-mean-square error of approximation (RMSEA) (Steiger and Lind, 1980, Joseph et al., 2007), the standardized root-mean-square residual (SRMR) (Hu and Bentler, 1995), and the comparative fit index (CFI) (Bentler, 1990). Following the standard conventions for the model fit evaluation, the RMSEA results indicate a good fit with values below 0.05 and an acceptable fit with values between 0.05 and 0.08 (Browne and Cudeck, 1993). For CFI, the acceptable fit is indicated with values over 0.9 (Bentler and Bonnett, 1980). For SRMR, a good model fit is indicated with values 0.08 and below (Hu and Bentler, 1998). Hu & Bentler (1998) suggest that SRMR and one of another range of tests (which includes CFI) are sufficient as complementary tests for the goodness of fit. Therefore, we report on both SRMR and CFI. Hooper et al. (2008) note that CFI should be 0.95 or above in more modern research, but above 0.9 suggests it is not misspecified. The SRMR should be <0.05 or <0.08, which is still considered acceptable. Therefore, we have judged SEM Model 5 (post-adoption) (CFI=0.94; SRMR 0.047) and SEM Model 2 (post-adoption) (CFI = 0.971; SRMR = 0.052) as acceptable in terms of goodness of fit. In addition, Table 2 shows that all the models have a reasonable fit. SEM Models 4 (pre-adoption), 5 (post-adoption) and 6 (both models) use the broad definition of trust, including the trust of the Internet, trust in Government and trust. The use of the broad definition of trust does not substantially change the model fit.

SEM Models 2 and 5, which are post-adoption as a separate model, have a better fit based on CFI and SRMR. SEM Model 1, pre-adoption (narrow trust), provides a poorer fit. When combining pre-adoption and post-adoption in SEM Model 3, the fit is poorer. SEM Models 1 (pre-adoption, trust narrow), 4 (pre-adoption, trust broad), and 6 (both adoption models, broad trust) demonstrate lower CFI, and we judged the SRMR results and as having less goodness of fit. Overall, we are using the meta-analysis correlations as a starting point, so there is no expectation that fit would be particularly good, but they provided a valuable comparison of the fit between the different models.

We conducted the chi-square difference test to evaluate the relative fit of the alternate models.

4. RESULTS

Table 3 summarizes the results of our hypothesis testing for the meta-analysis. Examining the 95% confidence interval of each hypothesis, we found that most hypotheses were supported. The results for Table 3 show pre-adoption confidence interval is supported by all hypotheses. The post-adoption confidence interval is supported by all hypotheses except H8 (*intention to use* to *actual use*).

Hypothesis one, *perceived ease of use* was found to be significantly related to *intention to use the e-Government system* in the pre-adoption model ($\rho = 0.346$, p=0.000), post-adoption model ($\rho = 0.431$, p=0.000), and both pre-adoption and post-adoption combined ($\rho = 0.383$, p=0.000).

Hypothesis two, *perceived usefulness* was found to be significantly related to *intention to use the e-Government system* in the pre-adoption model ($\rho = 0.521$, p=0.000), post-adoption model ($\rho = 0.565$, p=0.000), and both pre-adoption and post-adoption combined ($\rho = 0.537$, p=0.000).

Hypothesis three, *attitude* was found to be significantly related to *intention to use the e-Government system* in the pre-adoption model ($\rho = 0.654$, p=0.000), post-adoption model ($\rho = 0.712$, p=0.000), and both pre-adoption and post-adoption combined ($\rho = 0.689$, p=0.000).

Hypothesis four, *trust* was found to be significantly related to *intention to use the e-Government system* in the pre-adoption model ($\rho = 0.272$, p=0.000). There are no data points related to *trust* and *intention to use* in the post-adoption model and pre-adoption and post-adoption combined, which is the pre-adoption model as there is no data in the post-adoption model ($\rho = 0.272$, p=0.000).

Hypothesis five, *perceived ease of use* was found to be significantly related to *perceived usefulness* in the pre-adoption model ($\rho = 0.450$, p=0.000), post-adoption model ($\rho = 0.573$, p=0.000), and both pre-adoption and post-adoption combined ($\rho = 0.497$, p=0.000).

Hypothesis six *perceived usefulness* was found to be significantly related to *attitude* in the pre-adoption model ($\rho = 0.582$, p=0.000), post-adoption model ($\rho = 0.619$, p=0.000), and both pre-adoption and post-adoption combined ($\rho = 0.601$, p=0.000).

Hypothesis seven, *perceived ease of use* was found significantly related to *attitude* in the pre-adoption model ($\rho = 0.482$, p=0.015), post-adoption model ($\rho = 0.220$, p=0.000), and both pre-adoption and post-adoption combined ($\rho = 0.369$, p=0.002).

Hypothesis eight, *intention to use the e-Government system*, was found to be significantly related to the *actual use of the e-Government system* in the pre-adoption model ($\rho = 0.630$, p=0.002). However, this was not supported in the post-adoption model ($\rho = 0.201$, p=0.511). The hypothesis was supported in both pre-adoption and post-adoption combined ($\rho = 0.338$, p=0.035).

Table 2. SEM models for the meta-analysis results

Model number	Stage of adoption	Trust factors Narrow = trust Broad = trust all types of trust	Chi-Square Value Df p-value	RMSEA (root mean square error of approximation) Estimate	Probability RMSEA	CFI	SRMR
SEM Model 1	Pre-	Narrow	252.00 5 df p value 0.0000	0.519	0.000	0.563	0.130
SEM Model 2	Post-	Narrow	9.587 3 df p value 0.0224	0.119	0.070	0.971	0.052
SEM Model 3	Both	Narrow	33.978 5 df p value 0.0000	0.184	0.000	0.894	0.073
SEM Model 4	Pre-	Broad	371.07 5 df p value 0.0000	0.618	0.032	0.771	0.132
SEM Model 5	Post-	Broad	26.46 5 df p value 0.0001	0.160	0.001	0.940	0.047
SEM Model 6	Both	Broad	64.717 5 df p value 0.000	0.256	0.000	0.841	0.077

In total, we found significant relationships for 22 of the 23 variables. Only one variable, *intention to use* to *actual use* in the post-adoption model, failed to research statistical significance. All the variables were found significant in the predicted directions.

In Table 3, the confidence intervals for both pre-adoption and post-adoption studies of e-Government are different. However, when both post- and pre-adoption are combined into the joint model, the confidence intervals cover an overlap between the post- and pre-adoption data.

5. DISCUSSION

Research has been ongoing in the e-Government area, and several meta-analytic studies have been published. However, the prior meta-analysis models have combined the pre-adoption and post-adoption data. This paper has separated the pre-and post-adoption and shown that these models are distinct.

5.1 Meta-Analysis Discussion

In this meta-analysis, we found that most hypotheses were supported. Table 3 summarizes the results of our hypothesis tests. Hypothesis 8, *intention* to use to *actual use*, was not supported for the post-

Table 3. Summary and hypothesis testing

Hypothesis	Total sample size for the given meta-analysis (K)	Number of studies included in the meta-analysis (N)	Corrected population correlation (ρ)	95% Confidence Interval Lower Upper	Effect size (p)	Result
Intention to use						
H1: Perceived ease of use						
Pre	25	7,938	0.346*	0.187 0.4878	0.000	Supported
Post	17	65,421	0.431*	0.352 0.503	0.000	Supported
Both	42	73,359	0.383*	0.313 0.448	0.000	Supported
H2: Perceived usefulness						
Pre	28	8,349	0.521*	0.411 0.617	0.000	Supported
Post	16	67008	0.565	0.442 0.666	0.000	Supported
Both	44	75,357	0.537*	0.445 0.618	0.000	Supported
H3: Attitude						
Pre	8	2,992	0.654*	0.385 0.820	0.000	Supported
Post	9	2,062	0.712*	0.518 0.836	0.000	Supported
Both	17	5,054	0.689*	0.554 0.789	0.000	Supported
H4: Trust						
Pre	10	2008	0.272*	0.150 0.387	0.000	Supported
Post						
Both	10	2008	0.272*	0.150 0.387	0.000	Supported
Perceived usefulness						
H5: Perceived ease of use						
Pre	20	5,567	0.450*	0.289 0.587	0.000	Supported
Post	11	4,010	0.573*	0.412 0.700	0.000	Supported
Both	31	9,577	0.497*	0.386 0.593	0.000	Supported
Attitude						
H6: Perceived usefulness						
Pre	8	12,877	0.582*	0.489 0.684	0.000	Supported
Post	9	8,217	0.619*	0.505 0.705	0.000	Supported
Both	17	21,094	0.601*	0.538 0.656	0.000	Supported
H7: Perceived ease of use						
Pre	6	2,688	.482*	0.101 0.789	0.015	Supported
Post	6	1,899	.220*	0.144 0.292	0.000	Supported
Both	12	4,587	.369*	0.138 0.562	0.002	Supported
Actual use						
H8: Intention to use						
Pre	3	531	0.630*	0.271 0.835	0.002	Supported
Post	5	831	0.201*	-0.384 0.671	0.511	Unsupported
Both	8	1,362	0.338*	0.028 0.658	0.035	Supported

adoption model. The two models of pre-adoption and post-adoption discussed using the distinct models. This is discussed further below.

One benefit of meta-analysis is the ability to examine the strength of the relationships between constructs. The meta-analysis quantifies the strength and magnitude of the relationship between the two constructs. The general guidelines to judge the effect sizes are by looking at the values of the correlation coefficient. Correlation coefficients are not precise but are generally classified as weak, moderate, and strong. In our study, we assumed 0.00-0.09 to be insignificantly insignificant, 0.10-0.29 to be weakly significant, 0.30-0.49 to be moderately significant, 0.50-0.69 to be moderately significant (Cohen and Cohen, 1983). Thus, we see hypothesis 1 as moderately significant, and hypotheses 2, 3, and 6 are strongly significant. Hypothesis 4, which only relates to pre-adoption and includes the trust factor, is weakly significant. In the post-adoption studies, trust was not measured, which shows a difference between the pre-adoption and post-adoption studies. It also shows they are distinct and should be analyzed separately. For hypotheses 5 and 7, pre-adoption was moderately significant, and post-adoption was strongly significant. Hypothesis 8 showed pre-adoption was strongly significant, and post-adoption was not supported.

5.1.1 Trust

Hypothesis four relating to *trust* only relates to pre-adoption and not to post-adoption studies. When the data from the underlying studies were split between pre-adoption and post-adoption, it became evident that *trust* was only present in the pre-adoption studies. Therefore, the variable *trust* was not included in the post-adoption model for the meta-analysis. This is a difference between the two adoption models. Reviewing the underlying papers coded for post-adoption, *trust* is considered in many papers and only discussed in a few papers, but is not included in any paper as part of the empirical model.

Theoretically, trust was considered in the underlying papers studying pre-adoption as two types of trust, trust in the Government (e.g., confidence in the Government) and trust in the Internet (e.g., covers data security and privacy of a citizen's data, or enabling technologies significant to the citizen's intention to adopt the system). These forms of trust were discussed in the pre-adoption papers as early or initial trust.

However, there are discussions of trust in post-adoption underlying papers, but there is uncertainty about how much of a role trust plays in the intention to continue to use (Almahamid and McAdams 2010; Almahamid et al., 2010). All theoretical models of post-adoption from the underlying papers do not use the *trust* factor in their empirical models, and many do not even mention trust (Wangpipatwong et al., 2008; Thong et al., 2006; Fu et al., 2006). Almahamid and McAdams (2010) describe this as a belief that as soon as a citizen is satisfied with the e-Government site information, they will trust the e-Government site and continue to use the system. Other aspects suggested not tested in the post-adoption model but noted by some authors may play a role in continuance to use: perceived risk, demographical factors, culture (e.g., Wu et al., 2016 and Kumar et al., 2021) and political factors, and communication channels (Almahamid and McAdams, 2010).

Therefore, the overriding view seems that trust is frozen in the pre-adoption phase and is needed for continuous use. Nevertheless, if trust is lost, you would expect to see that continued use may not be possible. This would be an interesting angle for future research.

5.1.2 Actual Use

Hypothesis eight, which relates the *intention to use the e-Government system* to the *actual use*, provided some interesting findings. First, *intention to use* was significantly related to the *actual use* of the e-Government system in the pre-adoption model. As actual use does not occur in pre-adoption, this finding was surprising but reflected what several underlying papers had coded.

The most surprising finding was that the post-adoption model's *intention to use the e-Government system* positively influences the *actual use of the e-Government system* was not supported. Given all the studies performed on e-Government systems, it was disappointing that the actual use had hardly been studied. The point of e-Government implementation is the actual use of the system. The factors of *intention to use the e-Government system to actual uses* underlying data from five pairs of data from studies dated from 2009 to 2011. We expected more studies and greater use of actual use from 2011 to 2017, but none were present. Inspecting the underlying studies, Leung and Adams (2009) found a negative correlation between intention and actual use, which they noted as contrary. Still, they did not have an explanation for it. They had a small sample size. Zhang et al. (2011) broke their actual use into two groups, those that had not used the system before and those that had used the system before the training, which was the point at which they collected the data. They found no support for the hypothesis of users who had not used the system before the training. They found support for the hypothesis of the users who had used it before the training. Lu, Huang and Lo (2010) and Hu et al. (2011) found a positive correlation. Wang and Shih (2009) also found support for the hypothesis overall; however, they broke their study sample into genders and age groups. They found that the correlation for younger people was negative for intention to use to actual use. There was a slight gender bias towards females over males. Overall, the individual studies relating to hypothesis eight, *intention to use* to *actual use*, gave conflicting evidence, with few studies present. There are not large sample sizes in these studies. In the latter years, such as 2015, there are still more pre-adoption than post-adoption studies which is unusual given the increasing prevalence of e-Government systems.

To conclude from this, more studies need to measure behavioral intention to actual use to see if this factor is different in the e-Government field versus other fields. Zhang et al. (2011) attributed the drop in the e-Government system's use to the system's fit to the business and called it the declining phase. The need to measure actual use is, therefore, another area for future research.

5.2 MASEM

Researchers have combined meta-analysis and structural equation modeling (SEM) techniques to address unique research questions (Landis, 2013). We have used the meta-analysis structural equation modeling (MASEM) to test pre-adoption and post-adoption models and a combined model for model fit. Meta-analytic correlations are used from Table 3 as input for testing a structural model not evaluated in any single primary study (Viswesvaran and Ones, 1995). Therefore, the meta-analysis was input for the structural equation modeling analysis. For example, a meta-analysis can provide an empirical study that reports the correlation between A and B. Then another study that reports a correlation between B and C and another between A and D, B and D. Even though no one study reports all the correlations; we can meta-analyze these results and use them as estimates as correlations in the SEM.

There are cautions regarding what inferences can be reasonably drawn. Therefore, Structural Equation Modeling (SEM) models for the pre-adoption, post-adoption, and both (included both pre-adoption and post-adoption) were created using the Mplus software.

There are several critical questions that researchers need to consider when integrating meta-analysis and structural equation modeling. The critical question regarding the use of MASEM is ensuring that the studies use similar terminology. We can ensure this in our study as the underlying studies used TAM. TAM has constructs that have been validated, and established terms mean the same thing in each study.

The second task that needs to be done before SEM data analysis is a model that should already be clearly articulated. For example, we had the model in Figure 1 that was proposed for the meta-analysis. Therefore, we had this model before we performed the SEM analysis.

The sample size for MASEM was calculated using harmonic means, calculated as the reciprocal of the arithmetic mean of each of the reciprocals of each cell's sample size. Thus, the harmonic mean use limits the influence of some studies with large sample sizes and increases the influence of studies with smaller sample sizes.

The last question/issue to resolve before using MASEM relates to handling missing values in the input correlation matrix. As Figure 1 shows the research model, the *actual use* factor was related to *the intention to use* factor. There were no relationships between the *actual use* factor and *perceived* *usefulness, perceived ease of use*, and *trust.* Therefore, there were no correlations between these factors either. The literature's recommendations were to find studies with these correlations between these factors in meta-analysis source studies that you used and use the given correlations. Alternatively, if that yielded no values to identify studies that were not part of the meta-analysis and compute meta-analysis values from these. Or as a last resort, use values from single studies (Landis, 2013). The empty cells on the correlation matrix needed to be populated by values that provide a reasonable estimate. The Mplus software also did not allow a 0.000 correlation between factors either. This study used individual studies that had reported correlations between the two factors.

These models were run with the restricted factor of trust initially. Then, the models were re-run, including all the trust factors that prior meta-analysis had used and did not give any different answers on the model's strength. Finally, harmonic means were calculated for these models to be tested. The SEM model run with a broad and restricted definition of trust was very similar, which meant that prior studies' broad definition was reasonable.

The SEM analysis showed that the model for post-adoption by itself had a reasonable fit. However, when added with the pre-adoption model, the combined model has a lower fit. Therefore, the models of pre-adoption and post-adoption are reasonable as separate models. However, given that these models are based on the meta-analysis correlations, we exercise care when concluding from them.

5.3 Overall

One crucial element to note from the research data is that even in the latter years (such as 2015) when e-Government implementations have become common, there are still overwhelmingly more empirical papers on pre-adoption than post-adoption. One explanation may be that it remains easier to sample people based on their intention to use a system than to sample users of systems (e.g., collaborating with a government agency to reach the users). We do not believe there is a difficulty in accessing e-Government adopters. So, we are unsure why the lack of empirical studies, including post-adoption, is low. These studies can add value to the current literature in that the e-Government field has no cohesive direction. By looking at one research model, for example, expectations confirmation theory, we can reflect on that model's trends and discuss future research directions.

Linking back to this study's motivations, e-Government is vital, as many governments build these systems for their citizens to use. The use of the e-Government systems relates to the post-adoption use of the existing systems. Thus, it relates to actual use and intention to continue to use the system. The meta-analysis has shown that the most prevalent underlying model used is TAM, which has fallen in favor the information systems field (Benbasat & Barki, 2007).

Given the data on e-Government currently, TAM is the most prevalent model; it would be suggested that other post-adoption models may have more empirical studies and, therefore, be analyzed. It has been suggested that models such as Expectations Confirmation Theory, first articulated by Oliver (1980) and the updated by Bhattacherjee (2001) and Bhattacherjee and Premkumar (2004), would be better at looking at post-adoption models. This is a valid point, but a rise in the empirical research using the Expectations Confirmation Theory has not accompanied the decrease in TAM studies in the e-Government area. Once more empirical research has been performed using this theory in the e-Government area, a meta-analysis analyzing the post-adoption behavior using this model may give insights. However, encouraging the use of this model may be helpful too. Many different models have been used over time, and future directions may be more practical using one model. Our results also highlight the importance of government investments in, for instance, ICT infrastructure and other improvements that may support greater citizen e-participation (Ifinedo et al, 2021).

6. CONCLUSION

This meta-analysis of 53 studies used six variables drawn from TAM and provided several important contributions. The first theoretical contribution is how we have shown that while TAM is the most widely used model of e-Government system research, future research must change how we study this type of system. When analyzing the studies, it is important to examine the meta-analysis of e-Government to separate the pre-adoption studies from the post-adoption studies. In the post-adoption model, we found that *intention to use* was not statistically significant in affecting *actual use* due to Hypothesis 8 not being supported for post-adoption studies. Therefore, intention to use does not affect actual use.

Our second theoretical contribution is how we have shown that, despite the field's maturity, many studies continue to be published that relate to pre-adoption; the post-adoption studies we expected to increasingly see published were not present in our sample. Therefore, the number of relationships between *intention to use* and *actual use* was still very low.

The third theoretical contribution relates to our distinction between the types of trust relevant to e-Government systems. Prior studies included several forms of trust, such as trust in the Internet, the trust of the e-Government system, and general trust. In the preliminary meta-analysis, we removed all the different trust types and only had *trust* (called trust narrow). When the MPlus SEM model was run, initially, it was run with the restricted view of trust. It was then run, including all trust types (called trust broad – including all trust factors). The fit of the model was still good. Therefore, the broader definition of trust as used in the prior meta-analysis studies was valid to use. The MPlus SEM model also showed that the post-adoption model had a better fit as a separate model rather than a pre-adoption model.

Our study also has important contributions to practice and the profession. e-Government models are about actual use and about the intention to use continuously. Even without the TAM models, there was a lack of studies on actual use and intention to continuous use. Governments are implementing e-Government systems and require systems with satisfactory experience and performance. Therefore, more empirical research should investigate at how to achieve these outcomes. Suggestions that expectations confirmation theory could enable the examination of continuing use of the e-Government systems. Therefore, enabling low usage to be examined rather than the adoption area, as long-term viability depends on continuous use rather than adoption.

Limitations and future study areas. This study evaluates e-Government systems' performance using a meta-analysis of secondary data available online via a search of ProQuest to identify significant studies in electronic Government from a citizen adoption perspective. It would be interesting to see if the results change if more post-adoption studies featuring actual use. Pre-adoption studies' prevalence when e-Government empirical studies began in approximately 2004 was expected. However, we did not expect to identify a strong publication level of pre-adoption studies in 2017. We investigated whether this was related to developing versus developed countries (i.e., developing nations delaying e-Government implementations) but found that many recent studies were based in developed countries and still studied pre-adoption. The meta-analysis only includes cross-sectional studies and does not capture a cyclic effect of how governments can monitor and then adjust policies influence behaviors in e-Government as shown by Gao et al. (2019) or other areas such as citizen protection (Wood et al., 2017). This study also did not capture all possible factors relevant to adoption such as national culture as studied by Kumar et al. (2020) and future research may include meta-analytic studies that examine the role of national culture on e-Government adoptions.

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APPENDIX A: COMPARISON OF THE PAPERS USED BY RANA ET AL. (2015) AND THOSE IN THIS META-ANALYSIS

Rana et al. (2015) papers used in their meta-analysis	Used in the current meta-analysis that was used in Rana (2015)	Papers that were not used in Rana (2015) but which we use in the current meta-analysis
Wang (2002)	Wang (2002)	Carter and Belanger (2004)
Lau (2004)		Chu, Hsiao, Lee and Chen (2004)
Chu et al. (2004)		Phang, Sutanto, Kankanhalli, Yan, Tan and Teo (2006)
Seyal and Pijpers (2004)		Schaupp and Carter (2005)
Tung and Rieck (2005)		Wu and Chen (2005)
Carter and Belanger (2005)	Carter and Belanger (2005)	Thong et al. (2006)
Phang et al. (2005)	Phang, Li, Sutanto, Kankanhalli, (2005)	Horst, Kuttschreuter & Gutteling (2007)
Fu et al. (2006)	Fu, Chao and Farn (2006)	Klomsiri (2008)
Hung et al. (2006)		Wangpipatwong et al. (2008)
Kim and Holzer (2006)	Kim and Holzer (2006)	Pong, Leung and Adams (2009)
Sun et al. (2006)		Tang and Chung (2009)
Phang et al. (2006)		Wangpipatwong et al. (2009)
Yao and Murphy (2007)	Yao and Murphy (2007)	Almahamid et al. (2010)
Hung et al. (2007)		Almahamid and McAdams (2010)
Dwivedi et al. (2007b)		Alomari (2010/2012)
Khoumbati et al. (2007)		Chan et al. (2010)
Lee and Lei (2007)	Lee and Lei (2007)	Lean et al. (2010)
Sahu and Gupta (2007)		Shareef, Archer, Vedmani, Sharan and Kumar (2010)
Dwivedi and Weerakkody (2007)		Al-Hujran, Al-dalahmeh and Aloudat (2011)
Lau and Kwok (2007)		Hu, Chen, Hu, Larson & Butierez (2011)
Dwivedi et al. (2007a)		Hussein, Mohamed, Ahlan & Mahmud (2011)
van Dijk et al. (2008)		Rokhman (2011)
Tan et al. (2008)		Starrord and Turan (2011)
Colesca and Dobrica (2008)		Venkatesh et al. (2011)
Li et al. (2008)		Baker, Al-Gahtani & Hubona (2012)
Pinho and Macedo (2008)		Chiang (2012
Belanger and Carter (2008)		Rehman, Esichaikul and Kamal (2012)
Teo et al. (2008)		Rufin, Medina & Figureroa (2012)
Vathanophas et al. (2008)		Tan, Benbasat and Cenfetelli (2012)
Wang and Liao (2008)		Zafirpoulos, Karavasillis and Vrana (2012)
Carter (2008)	Carter (2008)	Udo, Bagchi and Kirs (2012)
Gotoh (2009)		Emad Abu-Shanab (2014)

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Rana et al. (2015) papers used in their meta-analysis	Used in the current meta-analysis that was used in Rana (2015)	Papers that were not used in Rana (2015) but which we use in the current meta-analysis
Yeow and Loo (2009)		Shareef, Kuman, Kumar and Dwivedi (2014)
Tang et al. (2009)		Jiang and Ji (2015)
Ojha et al. (2009)	Ojha, Sahu and Gupta (2009)	Seyal and Pijpers (2015)
Chiang (2009)		
Wang and Shih (2009)		
Hung et al. (2009)		
Gumussoy and Calisir (2009)		
Lean et al. (2009)	Lean, Sailani, Ramayah and Fernando (2009)	
Sang et al. (2009)		
Al-Shafi and Weerakkody (2009)		
Teerling and Pieterson (2010)		
Lu et al. (2010)	Lu, Huang & Lo (2010)	
Hussein et al. (2010)	Hussein, Mohamed, Ahlan, Mahmud and Aditawarman (2010)	
Sambasivan et al. (2010)		
Floropoulos et al. (2010)		
Liu and Zhou (2010)		
Schaupp and Carter (2010)		
Schaupp et al. (2010)		
Karavasilis et al. (2010)	Karavasillis, Zafiropoulos, Vrana (2010)	
Dorasamy et al. (2010)	Dorasamy, Marimuthu, Raman and Koliannan (2010)	
Sang et al. (2010)	Sang, Lee and Lee (2010)	
Rokhman (2011)		
Orgeron and Goodman (2011)	Orgeron and Goodman (2011)	
Al-Sobhi et al. (2011)		
Susanto and Goodwin (2010)		
Styven et al. (2011)		
Carter et al. (2011)		
Lin et al. (2011)		
Zhang et al. (2011)	Zhang, Guo, Chen (2011)	
Hu et al. (2011)		
Sipior et al. (2011)	Sipior, Ward and Connolly (2011)	

APPENDIX B: CONSTRUCTS CONTAINED IN THE INITIAL DIAGRAM/ MODEL OF E-GOVERNMENT ALONG WITH THEIR RELATIONSHIPS. (ADAPTED FROM RANA ET AL., 2015, PP. 550-551)

ACC: Accuracy	AG: Age	ANX: Anxiety
API: Avoidance of Personal Interaction	ASR: Assurance	ASS: Assistance
TT: Attitude	AU: Actual Use	AVL: Availability
AWR: Awareness	BA: Broadband Access	BEH: Behavior
BEN: Benevolence	BI: Behavioral Intention	CA: Computer Anxiety
CEXP: Citizen Expectation	COM: Compatibility	COMP: Complexity
COMT: Competence	CON: Convenience	CS: Computing Support
CT: Cost	DC: Declining Cost	DMA: Digital Media Access
DME: Digital Media Experience	DMP: Digital Media Preference	DPC: Declining Physiological Condition
DT: Disposition to Trust	ED: Education	EE: Effort Expectancy
EI: External Influence	EGA: E-Government Adoption	EMP: Empathy
EPE: External Political Efficacy	FC: Facilitating Conditions	FD: Future Development
FI: Family Influence	FLX: Flexibility	FP: Family Position
FRI: Friend Influence	FU: Future Use	GEN: Gender
HO: Hedonic Outcome	IC: Internet Competence	ICU: Intention to Continue Using
IE: Internet Experience	II: Interpersonal Influence	IT: Internet Trust
IIT: Innovativeness of IT	IMG: Image	INC: Income
IPC: Internal Political Efficacy	IQ: Information Quality	ISP: Internet Safety Perception
IU: Internet Use	IUWI: Internet Use Web Information	IUWT: Internet Use Web Transformation
INTG: Integrity	JR: Job Relevance	KS: Knowledge Services
MOB: Mobility	MT: Motivators	OB: Optimism Bias
PBC: Perceived Behavioral Control	PC: Perceived Credibility	PCN: Perceived Concerns
PCT: Perceived Cost	PCV: Perceived Convenience	PE: Performance Expectancy
PEN: Perceived Enjoyment	PER: Persuasion	PET: Previous E-Government Transaction
PEOU: Perceived Ease of Use	PES: Perceived Ease of Obtaining Subscription	PHC: Preference for Human Contact
PI: Personal Innovativeness	PIN: Primary Influence	PLN: Perceived Lack of Need
PK: Perceived Knowledge	PNB: Perceived Net Benefit	POT: Perceived Organizational Trustworthiness
PPR: Perceived Personal Relationship	PQ: Perceived Quality	PQT: Functional Value (Perceived/Quality) Perceived in Electronic Channel
PQ: Perceived Quality	PR: Perceived Risk	PRM: Performance
PRT: Perceived Trust	PRV: Privacy	PS: Perceived Security
PSC: Perceived Sacrifice	PSOA: Perceived Strength of Online Authentication	PSON: Perceived Strength of Online Non-Repudiation

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ACC: Accuracy	AG: Age	ANX: Anxiety
PSOP: Perceived Strength of Online Authentication	PT: Perceived Trustworthiness	PTR: Propensity to Trust
PU: Perceived Usefulness	PVP: Functional Value (Price/Value for Money) Perceived in Electronic Channel	RA: Relative Advantage
REL: Reliability	RESP: Responsiveness	RFC: Resource Facilitating Conditions
RFC: Resource Facilitating Conditions	RP: Risk Perception	RS: Resource Savings
SA: Self-Actualization	SAI: Structural Assurance of the Internet	SBT: Substitutability
SE: Self-Efficacy	SI: Social Influence	SIN: Secondary Influence
SN: Subjective Norm	SO: Social Outcome	SP: Societal Position
SQ: Service Quality	SRQ: Service Quality	SS: Supply Services
SSI: Secondary Source's Influence	STS: Satisfaction	SVP: Social Value Perceived in Electronic Channel
SYQ: System Quality	TA: Trusting Attitude	TB: Trusting Beliefs
TBS: Trusting Bases	TC: Technology Characteristics	TEF: Trust of the E-Filer
TEG: Trust in E-Government	TEGA: Trust in eGovernment Agent	TEGW: Trust in eGovernment Website
TFC: Technology Facilitating Conditions	TG: Trust of the Government	TI: Trust of the Internet
TIN: Trusting Intention	TOI: Trust of Intermediary	TRI: Training Impression
TRN: Training	TRST: Trust	TT: Trust in Technology
UB: Use Behavior	UO: Utilitarian Outcome	US: User Satisfaction
VPT: Value Perceived in Traditional Service Delivery Channel	WQ: Website Quality	WU: Website Usefulness
YIE: Years of Internet Experience]. [Types of Relationship Indicator: +: Significant; X: Non-Significant; and *: Mixed Relationship]		

APPENDIX C: ADAPTED FROM TABLE 1 IN RANA ET AL. (2015, P. 552) WITH THE WEIGHT ANALYSIS OF MOST FREQUENTLY USED RELATIONSHIPS. SHADING INDICATES THOSE RELATIONSHIPS USED IN THE CURRENT META-ANALYSIS

Independent variable	Dependent variable	Total	Significant relationships	Non-significant relationships	Weight
Perceived ease of use	Behavioral Intention	27	16	11	0.59
Perceived usefulness	Behavioral Intention	24	21	3	0.88
Perceived ease of use	Perceived Usefulness	20	18	2	0.90
Trust	Behavioral Intention	22	19	3	0.86
Attitude	Behavioral Intention	16	15	1	0.94
Perceived usefulness	Attitude	14	12	2	0.86
Perceived ease of use	Attitude	13	11	2	0.85
Behavioral intention	Actual use	10	10	0	1.00
Subjective norm	Behavioral Intention	9	9	0	1.00
Performance expectancy	Behavioral Intention	9	8	1	0.89
Social influence	Behavioral Intention	9	8	1	0.89
Effort expectancy	Behavioral Intention	9	7	2	0.78
Perceived behavioral control	Behavioral Intention	8	8	0	1.00
Relative advantage	Behavioral Intention	8	5	3	0.63
Compatibility	Behavioral Intention	8	6	2	0.75
Perceived risk	Behavioral Intention	7	4	3	0.57
Self-efficacy	Behavioral Intention	7	5	2	0.71
Compatibility	Attitude	7	1	7	0.86
Trust	Perceived Risk	6	4	2	0.67
Compatibility	Perceived Usefulness	6	4	2	0.67
Facilitating condition	Behavioral Intention	5	3	2	0.60

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Independent variable	Dependent variable	Total	Significant relationships	Non-significant relationships	Weight
System quality	Satisfaction	5	3	2	0.60
Service quality	Satisfaction	5	4	1	0.80
Job relevance	Perceived Usefulness	5	3	2	0.60
Facilitating Conditions	Perceived Behavioral Control	4	4	0	1.00
Self-efficacy	Perceived Behavioral Control	4	3	1	0.75
Relative advantage	Attitude	4	4	0	1.00
Image	Behavioral Intention	4	1	3	0.25
Image	Perceived Usefulness	3	2	1	0.67
Information quality	Satisfaction	3	2	1	0.67
Primary influence	Behavioral Intention	3	3	0	1.00
Facilitating condition resources	Behavioral Intention	3	3	0	1.00
Trust	Attitude	3	1	2	0.331
Perceived ease of use	Satisfaction	3	2	1	0.67
Self-efficacy	Perceived Ease of Use	3	3	0	1.00
Information quality	Perceived Usefulness	3	3	0	1.00
Perceived risk	Attitude	3	2	1	0.67

APPENDIX D: E-GOVERNMENT ADOPTION WITH MOST FREQUENTLY USED WEIGHTS ADAPTED FROM FIGURE 2 IN RANA ET AL. (2015, P. 553)

ATT attitude	AU Actual Use	BI behavioral intention
COMP compatibility	EE effort expectancy	FC facilitating conditions
FCR facilitating condition resources	IMG image	IQ information quality
IU intention to use	JR job relevance	PBC perceived behavioral control
PE performance expectancy	PEOU perceived ease of use	PI personal innovativeness
PR perceived risk	PU perceived usefulness	RA relative advantage
SE self-efficacy	SEQ service quality	SI social influence
SN subjective norm	STS satisfaction	SYQ system quality
TRST trust		

APPENDIX E: A COMPARISON OF PRE- AND POST-ADOPTION STUDIES

Study name in date order	Number of studies used	Pre/Post Adoption
Wang (2002)	1	Post
Carter and Belanger (2004)	1	Pre
Chu, Hsiao, Lee and Chen (2004)	1	Post
Carter and Belanger (2005)	1	Post
Phang, Sutanto, Kankanhalli, Yan, Tan and Teo (2006)	1	Pre
Phang, Li, Sutanto, Kankanhalli, (2005)	1	Pre
Schaupp and Carter (2005)	1	Pre
Wu and Chen (2005)	1	Pre
Fu, Chao and Farn (2006)	3	Study 1 – Pre Study 2 – Post Study 3 - Post
Kim and Holzer (2006)	1	Post
Thong et al. (2006)	1	Post
Horst, Kuttschreuter & Gutteling (2007)	1	Pre
Lee and Lei (2007)	1	Pre
Yao and Murphy (2007)	1	Pre
Carter (2008)	1	Pre
Klomsiri (2008)	1	Pre
Wangpipatwong et al (2008)	1	Post

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Study name in date order	Number of studies used	Pre/Post Adoption
Lean, Sailani, Ramayah and Fernando (2009)	1	Pre
Ojha, Sahu and Gupta (2009)	1	Pre
Pong, Leung and Adams (2009)	1	Post
Tang and Chung (2009)	1	Pre
Wangpipatwong et al. (2009)	1	Post
Almahamid et al. (2010)	2	Both Post
Almahamid and McAdams (2010)	1	Post
Alomari (2010/2012)	2	Both Pre
Chan et al. (2010)	1	Pre
Dorasamy, Marimuthu, Raman and Koliannan (2010)	1	Pre
Hussein, Mohamed, Ahlan, Mahmud and Aditawarman (2010)	1	Post
Karavasillis, Zafiropoulos, Vrana (2010)	1	Pre
Lean et al. (2010)	1	Pre
Sang, Lee and Lee (2010)	1	Pre
Shareef, Archer, Vedmani, Sharan and Kumar (2010)	1	Pre
Lu, Huang & Lo (2010)	1	Post
Al-Hujran, Al-dalahmeh and Aloudat (2011)	1	Pre
Hu, Chen, Hu, Larson & Butierez (2011)	1	Post
Hussein, Mohamed, Ahlan & Mahmud (2011)	1	Pre
Orgeron and Goodman (2011)	1	Post
Rokhman (2011)	1	Pre
Starrord and Turan (2011)	1	Pre
Venkatesh et al. (2011)	1	Post
Zhang, Guo, Chen (2011)	1	Post
Sipior, Ward and Connolly (2011)	1	Pre
Baker, Al-Gahtani & Hubona (2012)	1	Pre
Chiang (2012)	1	Pre
Rehman, Esichaikul and Kamal (2012)	1	Pre
Rufin, Medina & Figureroa (2012)	4	Pre
Tan, Benbasat and Cenfetelli (2012)	1	Post
Zafirpoulos, Karavasillis and Vrana (2012)	1	Pre
Udo, Bagchi and Kirs (2012)	1	Pre
Emad Abu-Shanab (2014)	1	Post
Shareef, Kuman, Kumar and Dwivedi (2014)	1	Pre
Jiang and Ji (2015)	1	Post
Seyal and Pijpers (2015)	1	Pre

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