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E-government adoption in sub-Saharan Africa

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ABSTRACT

Over the past decade, there has been increased interest in understanding the underlying factors that influence the adoption of e-government services using a variety of technology acceptance models. One such model is the *unified model of electronic government adoption* (UMEGA), which has been validated as outperformed other models. The present study empirically tested UMEGA and an extended version of it using data from 282 respondents in a sub-Saharan African country, South Africa. The findings show that except for the association of effort expectancy with attitude, all other hypothesized associations of UMEGA were supported. Also, the extended version of the model performed better than the original version, with the total variance explained for attitudes modestly increasing and that for behavioral intention modestly improving also. We observed that performance expectancy, social influence, perceived risk and computer self-efficacy significantly influenced attitudes, while attitudes, facilitating conditions, trust of government and trust of the Internet had a direct significant influence on behavioral intention. For researchers, this study indicates the need to adequately refine e-government adoption models for use in different context. These findings from South Africa also provide an understanding of factors that the South African government can consider when developing strategies for improving the adoption of e-government services.

1. Introduction

Many governments around the world are increasingly taking advantage of developments in *information and communication technologies* (ICTs) to offer online services to their citizens. This process is generally termed as e-government, which can be broadly defined as government's use of ICTs and its applications to deliver services and information to various stakeholders such as citizens and businesses (Lavanya and Gayatri, 2015; Padmapriya, 2013). E-government has been known to provide significant benefits, especially to citizens (Dwivedi et al., 2017). As such, many researchers and practitioners have been increasingly interested in understanding citizens' adoption of available e-government systems.

E-government researchers over the years have examined the adoption of e-government via existing technology acceptance models such as the *theory of reasoned action* (TRA) used by Alryalat et al. (2015) in India. In addition, the *theory of planned behavior* (TPB) was used by Ozkan and Kanat (2011) in Turkey, the *decomposed theory of planned behavior* (DTPB) was used by Susanto et al. (2017) in Indonesia, and the *technology acceptance model* (TAM) was used by Lin et al. (2011) in Gambia. Further, the extended version of TAM (TAM2) was used by Sang et al. (2009) in Cambodia, *diffusion of innovation theory* (DOI) was used by Lawson-Body et al. (2014) in the United States, and the *perceived characteristics of innovation* (PCI) was used by Boon et al. (2013) in Malaysia. Beyond these, *social cognitive theory* (SCT) WAS used by Rana and Dwivedi (2015) in India, the *unified theory of acceptance and use of technology* (UTAUT) was used by Rabaai (2017) in Jordan, and the extended UTAUT (UTAUT2) was used by Lallmahomed et al. (2017) in Mauritius.

Most of these concepts were adapted from the prior e-commerce adoption literature, owing to the close link between e-commerce and e-government solutions. However, some scholars (Alghamdi and Beloff, 2014; Shareef et al., 2011) have argued that models simply adopted from e-commerce literature are not sophisticated enough to fully capture and stipulate the comprehensive nature of citizens' e-government adoption behaviors. Consequently, domain-specific e-government adoption models, some of which are the *e-government adoption model* (GAM) by Shareef et al. (2011), the *e-government adoption and utilization model* (EGAUM) by Alghamdi and Beloff (2014) and the *unified model of electronic government adoption* (UMEGA) by Dwivedi et al. (2017) have been developed to address shortfalls of existing technology adoption models.

In sub-Saharan Africa (SSA), the majority of researchers evaluating e-government adoption to date have primarily focused on TAM (Asianzu and Maiga, 2012; Bwalya, 2011; Khanyako and Maiga, 2013; Komba and Ngulube, 2015; Lin et al., 2011; Rukiza et al., 2011). A key

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challenge with too much reliance on TAM is that many other factors that can explain e-government adoption, are left out. This follows from the argument by Benbasat and Barki (2007) that too much dependence on TAM basically creates an illusion of advances in new knowledge creation, while thwarting researchers from identifying new dimensions of technology adoption. As such, a recent study from SSA by Lallmahomed et al. (2017) which combined UTAUT and GAM to examine e-government adoption dimensions in Mauritius is quite timely and necessary.

There is still a huge gap in the literature from SSA with respect to validating other models like EGAUM and UMEGA in the region though. They may provide new insights in e-government adoption. Unlike EGAUM, which is quite complex with numerous moderating relationships, UMEGA is a more parsimonious and comparatively simpler model that balances the trade-off between model complexity and explanative power. The validation of UMEGA showed that it outperformed all other models for the explanatory power of the behavioral intention to adopt e-government solutions (Dwivedi et al., 2017).

This study focuses on UMEGA as a valuable e-government adoption model that can bring new insights for understanding e-government adoption in SSA. Consequently, the main objectives of this study are to: validate UMEGA in the SSA context; and modify UMEGA with relevant e-government adoption dimensions pertinent for application in the SSA context.

2. E-Government adoption in SSA

SSA is the geographical area on the African continent that lies south of the Sahara Desert and consists of all African countries except for Algeria, Egypt, Libya, Morocco, and Tunisia, which constitute the North African Arab countries. SSA is one of the least developed regions with respect to e-government. Over the years, there have been several efforts to document e-government adoption in different SSA countries. While some of the researchers have presented only theoretical models (Bwalya and Healy, 2010; Jain and Akakandelwa, 2014), many more have carried out empirical studies on e-government adoption in SSA countries (Asianzu and Maiga, 2012; Bwalya, 2011; Komba and Ngulube, 2015; Lallmahomed et al., 2017; Lin et al., 2011; Rukiza et al., 2011; Yonazi et al., 2010). However, the majority of these empirical studies have been primarily based on TAM. Only Lallmahomed et al. (2017) adopted other theoretical models such as UTAUT2 and GAM, while Yonazi et al. (2010) used randomly selected variables.

The numerous empirical studies carried out on e-government adoption in SSA indicated some vital factors that influence e-government adoption in the region. However, the findings have not been consistent. For example, Rukiza et al. (2011) found that the perceived usefulness dimension of TAM model significantly influenced e-government adoption in Tanzania. Conversely, Komba and Ngulube (2015) established that the perceived usefulness was not significantly associated with e-government adoption in Tanzania. Similarly, Bwalya (2011) and Lin et al. (2011) found perceived ease of use to have a significant influence on e-government adoption in Zambia and Gambia respectively. However, Komba and Ngulube (2015) found no support for the influence of perceived ease of use on e-government adoption in Tanzania. Likewise, Lallmahomed et al. (2017) failed to find support for the significant influence of effort expectancy (an equivalence of perceived ease of use) on e-government adoption in Mauritius. Significant antecedents of e-government adoption that have been confirmed by at least two studies in SSA include: computer self-efficacy (Bwalya, 2011; Lallmahomed et al., 2017), perceived ease of use (Bwalya, 2011; Lin et al., 2011), perceived security (Khanyako and Maiga, 2013; Muraya, 2015), perceived trust (Asianzu and Maiga, 2012; Bwalya, 2011; Khanyako and Maiga, 2013; Rukiza et al., 2011), perceived usefulness/performance expectancy (Lallmahomed et al., 2017; Rukiza et al., 2011), social influence (Komba and Ngulube, 2015; Muraya, 2015) and website quality/system quality (Komba and Ngulube, 2015; Muraya, 2015). Consequently, it is imperative to take into consideration these factors when extending and validating e-government adoption models in the context of SSA.

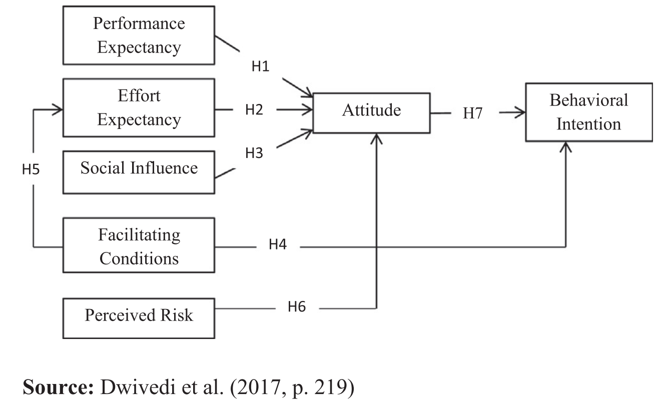

Fig. 1. The Unified Model of E-Government Adoption (UMEGA). .
Source: Dwivedi et al. (2017, p. 219)

3. Proposed research model and hypothesis development

Dwivedi et al. (2017) provided a comprehensive evaluation of nine well-known theoretical models covering 29 different constructs as the basis for developing UMEGA (see Fig. 1). Following from their evaluation, UMEGA was developed and validated as an e-government specific model that could be used to understand the factors influencing the acceptance of e-government services.

UMEGA postulates that four factors (performance expectancy, effort expectancy, social influence, and perceived risk) influence the behavioral intention to adopt e-government systems through the mediating role of attitudes towards e-government services. Also, attitudes and facilitating conditions directly influence behavioral intention, while facilitating conditions also has an indirect influence on attitudes through the mediating role of effort expectancy. UMEGA's variables are discussed below.

3.1. Umega's variables

3.1.1. Performance expectancy, effort expectancy, and social influence

Performance expectancy, effort expectancy and social influence are three factors that were initially conceptualized in UTAUT to evaluate technology adoption in the organizational context (Venkatesh et al., 2003) and later adopted and used in the creation of the UATUT2 to extend their applicability in a consumer context (Venkatesh et al., 2012). Performance expectancy refers to the extent to which an individual believes that using a given technology will enable him or her to accomplish improvements in completing a given task or job role (Venkatesh et al., 2012). This suggests that an individual's perception that using an e-government system will help to achieve gains in completing a government-provided service will influence their attitudes and intention to use the system. *Effort expectancy* refers to the "degree of ease associated with consumers' use of technology" (Venkatesh et al., 2012: 159), suggesting that an individual will generally be more inclined to adopt an e-government solution that requires minimal effort to use. *Social influence* refers to the degree to which an individual perceives that significant others (family, friends and colleagues) will approve of using a given technology (Venkatesh et al., 2012). This suggests that individuals will generally be inclined to adopt a given system if important others (family, friends and colleagues) approve of using such a technology.

Several studies have shown that *performance expectancy* has a significant influence on e-government adoption (Lallmahomed et al., 2017; Weerakkody et al., 2013). This association has not always been universal, as KrishnarajuSaji et al. (2016) failed to find support for a significant association between performance expectancy and e-government adoption in India. Also, even though *effort expectancy* (Venkatesh et al., 2012; Weerakkody et al., 2013) and social influence (Oliveira et al., 2016; Sumak and Sorgo, 2016; Weerakkody et al., 2013) have been shown to influence technology adoption, Lallmahomed et al. (2017) failed to find support for the significant positive influence of both effort expectancy and social influence on the behavioral intention to adopt e-government systems in Mauritius.

Similarly, Weerakkody et al. (2013) failed to find support for the significant role of social influence on e-government adoption in Saudi Arabia. Disparities in findings could arise from the theoretical view that performance expectancy, effort expectancy and social influence are associated with behavioral intention through the mediating role of the individual's attitudes towards adopting a given technology (Alshare and Lane, 2011; Lin et al., 2011; Park et al. 2007; Pynoo et al., 2011; Sumak and Sorgo, 2016). As such, UMEGA proposed and validated the theoretical conception that social influence, performance expectancy and effort expectancy influenced behavioral intention through their positive impact on attitudes towards adopting a given e-government system (Dwivedi et al., 2017). Thus, this study offers:

Hypothesis 1 (*(Performance expectancy-system use attitude):***).** *Performance expectancy has a positive and significant influence on attitudes toward using an e-government system.*

Hypothesis 2 (*(Effort expectancy-system use attitude):***).** *Effort expectancy has a positive and significant influence on attitudes toward using an e-government system.*

Hypothesis 3 (*(Social influence-system use attitude):***).** *Social influence has a positive and significant influence on attitudes toward using an e-government system.*

3.1.2. Facilitating conditions

Facilitating conditions depict the perceptions of users surrounding the resources and support that is available for conducting a given behavior (Venkatesh et al., 2012). In an e-government setting, facilitating conditions could embody the degree to which citizens believe that there are adequate resources available that can facilitate them to access an e-government service. In the development of UTAUT, Venkatesh et al. (2003) argued that facilitating conditions had an insignificant influence on technology adoption in an organizational context when controlling for the effect of factors like performance and effort expectancies. However, in a consumer context, facilitating conditions become relevant in predicting behavioral intention even in the presence of performance and effort expectancies, as shown in the development of UTAUT2 (Venkatesh et al., 2012). This view has also been supported when studying e-government adoption by citizens, as some studies (Carter et al., 2012; Dwivedi et al., 2017; Kurfali et al., 2017; Lallmahomed et al., 2017) have shown that facilitating conditions played a significant role in a citizen's intention to adopt e-government systems. Dwivedi et al. (2017) further conceptualized in UMEGA that facilitating conditions also had an indirect effect on attitudes towards e-government, through its influence on effort expectancy. As such, this study asserts:

Hypothesis 4 (*(Facilitating conditions-system use attitude):***).** *Facilitating conditions has a positive and significant influence on attitudes toward using an e-government system.*

Hypothesis 5 (*(Facilitating conditions-effort expectancy):***).** *Facilitating conditions has a positive and significant influence on effort expectancy.*

3.1.3. Perceived risk

Perceived risk generally denotes feelings of uncertainty or anxiety associated with using a given information system due to anticipated outcomes (Slade et al., 2015). In the context of e-government, perceived risk can be seen as the conviction by a citizen that he/she will suffer some sort of loss when using an e-government system. Given that systems like e-government websites need to be accessed via the Internet, some citizens might tend to limit their interactions with these websites due to Internet associated risk. For example, prior literature indicates that over 80% of Internet users are highly concerned about making personal identities known on the web (Rana et al., 2015; Schaupp and Carter, 2010). This can, therefore, have a limiting effect on citizen interaction with transactional e-government websites. Prior evidence indicates that perceived risk significantly affects attitudes towards adopting these technologies, such that consumers with high-risk perceptions are less likely to adopt e-government solutions (Dwivedi et al., 2017; Sulaiman et al., 2012; Susanto and Goodwin, 2011). As such, this study posits:

Hypothesis 6 (*(Perceived risk-system use attitude):***).** *Perceived risk has a negative and significant influence on attitude toward using an e-government system.*

3.1.4. Attitude and behavioral intention

The *attitude towards using a given information system* is defined as the positive or negative appraisal of an individual regarding the specific behavior (Dwivedi et al., 2017; Hung et al. 2013). In the context of e-government adoption, individuals with a positive appraisal of an e-government system will have a high intention of adopting the system and vice versa. The association between attitudes and behavioral intention has been validated in several e-government studies (Hung et al., 2013; Lu et al., 2010), including UMEGA (Dwivedi et al., 2017). As such, this study will assess:

Hypothesis 7 (*(Individual attitude-system use):***).** *An individual's attitude toward using an e-government system has a positive and significant relationship with intention to use the system.*

3.2. Extending UMEGA

While UMEGA is a unified model, prior research has shown that unified models such as UTAUT and UTAUT2 can be further modified by extending them with relevant factors that suit a given application context (Alalwan et al., 2017; Oliveira et al., 2016). Similarly, Dwivedi et al. (2017) also recognized the fact that UMEGA could benefit from further theoretical modifications to suit its applicability and implementation in other countries or regions. After our review of e-government adoption in SSA and UMEGA, it became evident that even though UMEGA captured many of the significant antecedents of e-government adoption in SSA, some pertinent adoption factors in the context of SSA were still missing from the model. Two of these factors were computer self-efficacy and perceived trust, which have been shown to be important by several studies in SSA (Asianzu and Maiga, 2012; Bwalya, 2011; Khanyako and Maiga, 2013; Lallmahomed et al., 2017; Rukiza et al., 2011). Consequently, this study proposes extending UMEGA with these factors to increase its applicability in the context of SSA. The proposed model is presented below (see Fig. 2).

3.2.1. Computer self-efficacy

Computer self-efficacy can be defined as "the judgment of an individual's ability to use a computer to perform a particular task" (Compeau and Higgins, 1995: 122). Even though this definition of computer self-efficacy dates over two decades back, it has been widely used and accepted by contemporary researchers (Chen, 2017; Yesilyurt et al., 2016). Computer self-efficacy in e-government depicts an individual's appraisal of his or her ability to successfully use a computer (or another technological tool such as a tablet or smartphone) to access an e-government service. Many e-government studies (Bwalya, 2011; Chatzoglou et al., 2015; Wangpipatwong et al., 2005; Zhao and Khan,

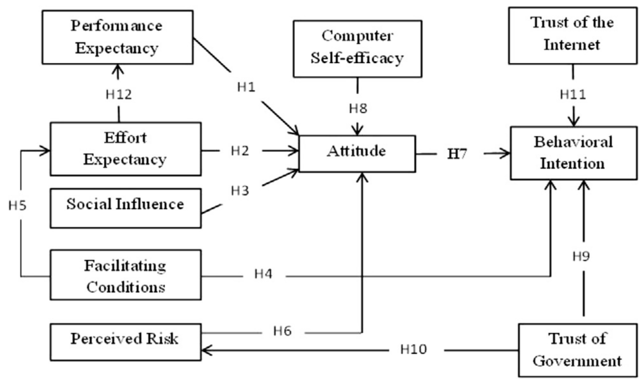

Fig. 2. Proposed modification of UMEGA.

2013) have shown that computer-self-efficacy is an important factor that influences the intention to adopt e-government systems.

Even though these studies have shown a direct association between computer-self efficacy and behavioral intention, as proposed in GAM (Shareef et al., 2011), the present study suggests that this association in the context of UMEGA should be mediated by attitudes towards adoption of e-government services. This follows from the existing evidence that shows computer self-efficacy to be an influential factor that shapes user attitudes towards using computers in different context (Lu et al., 2016; Yesilyurt et al., 2016), and the fact that attitude has been shown to instigate behavioral intention in UMEGA (Dwivedi et al., 2017). As such, this study suggests:

Hypothesis 8 (*(Computer self-efficacy-system use attitude):*). *Computer self-efficacy has a positive and influence significant influence on attitude toward using an e-government system.*

3.2.2. Trust

There is a general consensus that trust is instrumental in determining the adoption of Internet technologies (Abu-Shanab, 2017; Lallmahomed et al., 2017). However, trust is a multifaceted concept that spans several disciplines and thus is defined from different perspectives to suit the specific context. Nonetheless, the general foundation of trust posits that the promise made by one party can be relied upon by the other party (Zhao and Khan, 2013). In the context of e-government, *trust* is generally conceptualized using two factors, namely trust of government and trust of the Internet (Abu-Shanab, 2017; Lallmahomed et al., 2017; Zhao and Khan, 2013). *Trust of government* denotes the subjective degree to which citizens believe in the uprightness and ability of the government agency that provides the e-government service (Belanger and Carter, 2008; Lallmahomed et al., 2017), while *trust in the Internet* refers to the subjective extent to which citizens believe that using an online e-government system is secure and has no threat to their privacy (Abu-Shanab, 2017; Rehman et al., 2011).

Prior studies have shown that trust of government has a positive and significant direct influence on the intention to adopt e-government systems (Belanger and Carter, 2008; Lallmahomed et al., 2017; Rehman et al., 2011; Zhao and Khan, 2013), as well as an indirect influence through the mediation of perceived risk, such that higher trust of government minimizes the perceived risk of using a given e-government system (Belanger and Carter, 2008). Similarly, several studies have supported the positive and significant association of trust of the Internet and behavioral intention to adopt e-government services (Belanger and Carter, 2008; Kurfali et al., 2017). As such this study asserts:

Hypothesis 9 (*(Government trust-service adoption):*). *Trust of government has a positive and significant influence on the behavioral intention to adopted e-government services.*

Hypothesis 10 (*(Government trust-system risk):*). *Trust of government has a negative and significant influence on the perceived risk associated with using an e-government system.*

Hypothesis 11 (*(Internet trust-service adoption):*). *Trust of the Internet has a positive and significant influence on the behavioral intention to adopted e-government services.*

3.2.3. Association between effort expectancy and performance expectancy

Both UTAUT and UTAUT2 conceptualized performance expectancy and effort expectancy to have a direct positive influence on the behavioral intention to adopt a given technology (Venkatesh et al., 2012). In the same light, the conceptualisation of UMEGA followed the same trend with the only difference being the introduction of attitudes as a mediating factor in the associations (Dwivedi et al., 2017). However, prior research has widely questioned the significance of the association between effort expectancy and behavioral intention, as many studies have shown the association to be insignificant (Lallmahomed et al., 2017; Morosan and DeFranco, 2016; Oliveira et al., 2016). In fact, most researchers have increasingly shown that the association between effort expectancy and behavioral intention is instead indirect, via the mediating role of performance expectancy (Alalwan et al., 2017; Herero, Martin and Salmones, 2017; Oliveira et al., 2016). As such, this study offers:

Hypothesis 12 (*(Effort expectancy-performance expectancy):*). *Effort expectancy has a positive and significant influence on performance expectancy.*

Hypothesis 13 (*(Effort expectancy-system use attitude):*). *Effort expectancy has a positive and significant total indirect effect on attitudes toward using an e-government system.*

4. Methodology

4.1. The context of the study

South Africa was selected as the SSA context for testing and validating UMEGA and its modified version. This choice was based on the ease with which the researchers could obtain suitable data. South Africa is one of the leading countries in SSA with respect to e-government development. The 2016 e-Government Development Index (EGDI) ranked South Africa (EGDI = 0.56) second to Mauritius (EGDI = 0.62) in SSA (UNDESA, 2016). This was an improvement compared to the 2012 EGDI when South Africa (EGDI = 0.49) was in the third position, behind Seychelles (EGDI = 0.52) and Mauritius (EGDI = 0.507), respectively.

Even though South Africa is in the top tier of e-government development in SSA, it is also plagued by several challenges that are common across SSA countries. For example, the South African government has made several efforts in implementing e-government systems, yet, one of the key challenges in e-government diffusion in the country is the slow uptake of e-government services (Mawela et al., 2017; Mutula and Mostert, 2010). This pattern of slow adoption of e-government services was also recorded in other SSA countries. They include: Gambia (Lin et al., 2011); Kenya (Muraya, 2015); Mauritius (Lallmahomed et al., 2017); Uganda (Khanyako and Maiga, 2013); Tanzania (Komba and Ngulube, 2015; Rukiza et al., 2011); and Zambia (Bwalya, 2011). Given that prior studies have shown that South Africa leads SSA with respect to the provision of online services (Rorissa and Demissie, 2010; Verkijika, 2017), it would be interesting to see the factors that influence e-government adoption in this country, as this could not only help improve uptake of e-government services in the country but also serve as a learning curve for other SSA countries.

4.2. Measurements

A quantitative study was developed to test the research hypotheses based on UMEGA and its modified version. Data were collected from respondents in the Bloemfontein Area of South Africa, using a survey approach. Items for the questionnaire were drawn from existing literature (see Appendix A). The items for behavioral intentions, performance expectancy, effort expectancy, social influence, and facilitating conditions were adapted from Dwivedi et al. (2017), Kurfali et al. (2017), Lallmahomed et al. (2017) and Venkatesh et al. (2012). Items for attitude and perceived risk were adapted from Dwivedi et al. (2017). Items for trust of government and trust of the Internet were adapted from Kurfali et al. (2017) and Lallmahomed et al. (2017), while items for computer-self efficacy were adapted from Lallmahomed et al. (2017). Each item was measured on a five-point scale ranging from 1 (strongly agree) to 5 (strongly disagree). Three demographic variables were measured namely age, gender, and education. The same questionnaire was used to evaluate UMEGA and the proposed extension as the extension simply adds new dimensions and associations, while retaining all the hypothesized paths in UMEGA.

4.3. Data

A convenience sample was used to collect data from respondents. A total of 450 questionnaires were issued from which 282 valid responses were obtained, a 62.7% valid response rate). As with Lallmahomed et al. (2017), only respondents from 18 years of age were selected because they are the most likely group to use e-government services. The majority of the respondents were the younger generation, below 30 years of age (51.8%). This age distribution is quite similar to that used in evaluating UMEGA as 61% of their respondents were below 30 years (Dwivedi et al., 2017). Similarly, the respondents of the e-government adoption study in Mauritius by Lallmahomed et al. (2017) had 60.8% respondents below 30 years. The majority of the respondents were female (54.3%). Also, 68.1% of the respondents had completed at least an undergraduate degree. A detailed breakdown of the demographic data is presented in Table 1.

5. Data analysis and results

5.1. Measurement model

The two structural models, UMEGA and modified UMEGA, were tested using *partial least squares structural equation modeling* (PLS-SEM) approach. Generally, the PLS-SEM approach is very useful in validating models that have not been widely tested in prior literature and are complex in nature (Oliveira et al., 2016). Also, the PLS-SEM approach takes into account measurement error and provides results that are more accurate than regression (Gefen et al., 2011). As such, given the need for accurate results and the fact that the proposed modified version of UMEGA is a complex model that has not been previously explored in the extant literature, the PLS-SEM approach was deemed most suitable. As such, SMART PLS 3.0 (Ringle et al., 2015) was selected as the evaluation tool, as the tool has been widely validated in several studies that test proposed models (Cocosila and Trabelsi, 2016; Lallmahomed et al., 2017; Oliveira et al., 2016) compared to approaches like AMOS and LISREL that are predominantly used for confirmatory testing (Cocosila and Trabelsi, 2016). Additionally, the SMART PLS tool provides readily available results for examining the total indirect effect which is vital in this study to evaluate the Effort Expectancy-System Use Attitude Hypothesis (H13) and also understand the total indirect effect of all the introduced variables in the modified version of UMEGA.

Table 1
Demographic information.

Gender	#	%	Education	#	%
Male	129	45.7	High school diploma or below	24	8.5
Female	153	54.3	Higher education diploma	66	23.4
Age	#	%	Undergraduate degree	124	44.0
18–25 years	94	33.3	Postgraduate (above degree)	68	24.1
26–29 years	70	24.8			
30–40 years	76	27.0			
Above 40 years	42	14.9			

Note: # is the frequency count.

Table 2
Quality criteria.

Construct	Cronbach's α	AVE	CR	Factor Loadings
Attitude (AT)	0.743	0.669	0.856	0.751 to 0.900
Behavioral intention (BI)	0.792	0.660	0.880	0.724 to 0.889
Computer self-efficacy (CS)	0.981	0.957	0.985	0.947 to 0.994
Effort expectancy (EE)	0.952	0.875	0.966	0.902 to 0.965
Facilitating conditions (FC)	0.907	0.785	0.936	0.789 to 0.943
Perceived risk (PR)	0.954	0.879	0.967	0.883 to 0.961
Performance expectancy (PE)	0.758	0.582	0.847	0.728 to 0.878
Social influence (SI)	0.817	0.731	0.890	0.808 to 0.880
Trust of government (TG)	0.920	0.863	0.950	0.909 to 0.920
Trust in the Internet (TI)	0.971	0.971	0.986	0.984 to 0.987

Several quality criteria were used to test the reliability and validity of the proposed model. These criteria are presented in Tables 2 and 3. Table 2 indicates the *composite reliability* (CR), Cronbach's α, *average variance extracted* (AVE) and factor loadings.

The general indicator for reliability with respect to factor loadings is that items should load above 0.7 (Hair et al., 2010). This was achieved, as can be seen from Table 2 where factor loadings ranged from 0.724 to 0.994. Additionally, there are no issues of cross-loadings as shown in Appendix B, as all the items loaded much higher in their intended constructs, suggesting that none of the indicators have been erroneously assigned to an incorrect factor (Henseler et al., 2016). Construct reliability was evaluated using Cronbach's α and composite reliability. With respect to Cronbach's α, constructs needed an αvalue of at least 0.7 (Henseler et al., 2009). This was achieved, as alpha values ranged from 0.743 to 0.981. Similarly, the criterion for composite reliability was based on the view that appropriate values should be above 0.8, even though values above 0.6 are acceptable (Henseler et al., 2009). All the composite reliability values as seen from Table 2 meet the 0.8 criteria, as the values ranged from 0.847 to 0.986. As such, both the Cronbach's α and composite reliability criteria were met, confirming the construct reliability of the factors. Also, the AVE was used to evaluate convergent validity based on the criteria that valid constructs should have AVE values above 0.5 (Hair et al., 2010). This criterion was also met as AVE values ranged from 0.582 to 0.971 (Table 2). Lastly, the discriminant validity of the constructs was also tested using the Fornell-Larcker criterion (Table 3) and the *heterotrait-monotrait ratio* (HTMT) presented in Table 4.

Table 3 presents the outcome of the discriminant validity based on the Fornell-Larcker criterion. According to this criterion, a construct is considered to have discriminant validity if the square root of the AVE (indicated in bold in Table 3) is greater than the paired inter-correlations between the latent constructs (Fornell and Larcker, 1981). It is observed from Table 3 that all the diagonal variables (square root of the AVE) are higher than the corresponding off-diagonal values (paired inter-correlations). As such, all the constructs satisfied the Fornell-Larcker criterion, thus confirming the discriminant validity of the scales used. Following recommendations from prior studies (Henseler et al., 2016; Lallmahomed et al., 2017), the HTMT was also examined to ascertain the discriminant validity of the constructs. Generally, discriminant validity is confirmed in PLS-SEM when the HTMT is < 1 (Henseler et al., 2016), although Kline (2011) suggests a value of 0.85 as the most conservative threshold for HTMT. The HTMT values are

Table 3
Fornell-Larcker Criterion: Correlations of constructs and square root of AVE (bold).

Variables	AT	BI	CS	EE	FC	PR	PE	SI	TG	TI
AT	**0.82**									
BI	0.70	**0.81**								
CS	0.13	0.16	**0.98**							
EE	0.06	0.14	−0.04	**0.94**						
FC	0.17	0.24	0.14	0.61	**0.89**					
PR	−0.22	−0.24	−0.10	−0.12	−0.09	**0.94**				
PE	0.34	0.47	0.20	0.18	0.44	−0.09	**0.76**			
SI	0.18	0.27	0.16	0.26	0.29	−0.08	0.15	**0.85**		
TG	0.21	0.31	0.08	0.15	0.20	−0.12	0.17	0.13	**0.93**	
TI	0.19	0.24	−0.05	0.08	0.05	−0.68	0.06	0.06	0.12	**0.99**

Table 4
HTMT criterion for discriminant validity.

Variables	AT	BI	CS	EE	FC	PR	PE	SI	TG
BI	0.81								
CS	0.06	0.10							
EE	0.08	0.17	0.06						
FC	0.21	0.31	0.05	0.65					
PR	0.25	0.28	0.05	0.13	0.09				
PE	0.47	0.66	0.24	0.21	0.53	0.11			
SI	0.21	0.34	0.18	0.30	0.34	0.10	0.18		
TG	0.25	0.38	0.05	0.16	0.22	0.13	0.21	0.15	
TI	0.22	0.27	0.04	0.08	0.05	0.72	0.08	0.08	0.13

indicated in Table 4. As shown in Table 4, it was observed that all the HTMT values were below the threshold value of 0.85 depicting that each pair of the factors clearly discriminates against each other. As such, both the Fornell-Larcker criterion (Table 3) and the HTMT (Table 4) results confirm the discriminant validity of the constructs.

Last, the dataset was assessed for common method bias using Harman's single factor test. All the items indicated in Appendix A were introduced in an exploratory factor analysis and the unrotated solution extracted according to the guidelines by Podsakoff et al. (2003). The Statistical Package for the Social Sciences (SPSS) tool was used to conduct the factor analysis. All the factors isolated through this approach explained 79.1% of the variance, with the largest variance explained by a single factor being 21.2%. All the variables did not load on a single factor, and no single factor explained more than 50% of the variance. As such, common method bias was not seen as a concern in the present study.

5.2. Structural model for the original UMEGA

Fig. 3 presents the structural model of UMEGA as proposed by Dwivedi et al. (2017). The bootstrap method with 5,000 sub-samples was used to generate the path coefficients and their significance levels using *t*-statistics. Of the seven hypotheses proposed in UMEGA, only the association between effort expectancy and attitude was not significant. It is also shown that UMEGA has a high predicting power on behavioral intention, as the total variance explained is 64.7%. However, the prediction of attitudes is not very strong, as the total variance explained is only 18.1%. With regard to the factors that predict attitudes, performance expectancy had the highest influence, with a standardized beta coefficient of 0.32, followed by perceived risk ($\beta = -0.19$) and social influence ($\beta = 0.13$). The structural model of the modified UMEGA is presented below to determine its applicability.

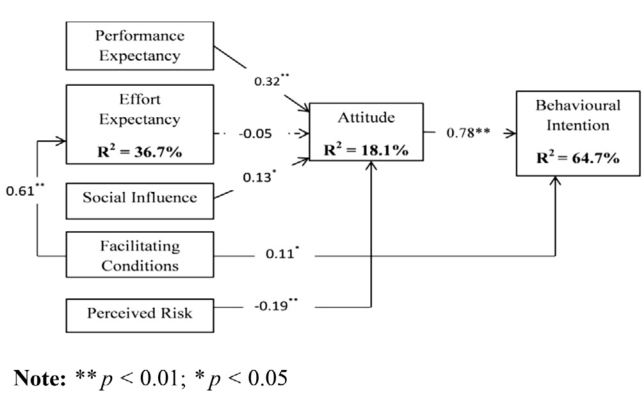

Fig. 3. Structural model of UMEGA. Note: ** $p < 0.01$; * $p < 0.05$.

5.3. Structural model for the modified UMEGA

Fig. 4 presents the structural model of the modified UMEGA proposed in this study.

The significance of the path coefficients was evaluated using *t*-statistics generated from the bootstrap method with 5000 sub-samples. Similar to the structural model of UMEGA, all the hypothesized paths of the original UMEGA were significant, except for the association between effort expectancy and attitude ($\beta = -0.05$; p greater than 0.05). The modified model showed significant gains both in the prediction of attitudes and behavioral intention. It was observed that the explanatory power of attitudes improved when the following associations were included: (1) the direct effect of computer self-efficacy on attitude; (2) the indirect effect of trust of government on attitude (mediated by perceived risk); and (3) the indirect effect of effort expectancy on attitude (mediated by performance expectancy). This is because the total variance explained for attitudes increased from 18.1% in the original UMEGA to 21.3% in the proposed modification (a 3.2% increase). Similarly, the modified UMEGA showed an improved prediction of behavioral intention following the addition of the direct effects of trust of government ($\beta = 0.13$; $p < 0.001$) and trust of the Internet

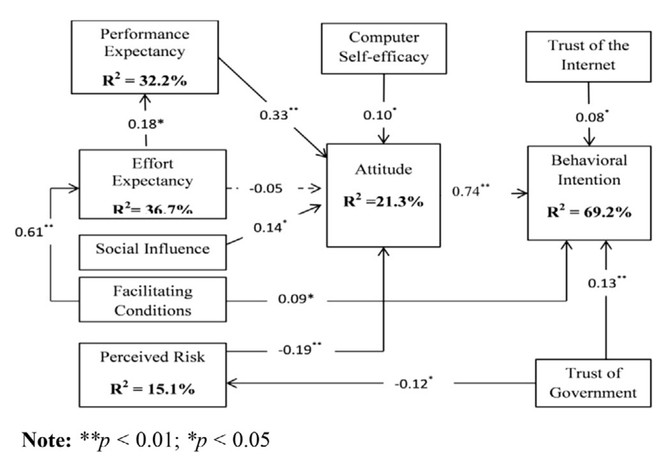

Fig. 4. Structural model of the modified UMEGA. Note: **$p < 0.01$; *$p < 0.05$.

Table 5
Total indirect effects introduced in the modified UMEGA.

Total indirect effect	Std path coef	Critical ratio	Signif (*p*)
EE → PE → AT	0.061*	2.456	0.014
TG → PR → AT	0.024	1.418	0.156
CS → BI	0.045*	2.229	0.026
Note: * $p < 0.05$			

($\beta = 0.08$; $p < 0.05$). This is because the total variance explained increased from 64.7% in the original UMEGA to 69.2% in the modified version (a 4.5% increase). The outcome of the hypotheses based on the proposed model is presented below.

In addition to the direct effects, the following indirect effects introduced in the modified UMEGA were also observed, as the results are automatically generated by SMART PLS when evaluating the proposed model.

From Table 5, it is observed that the total indirect effect of effort expectancy on attitude through the role of performance expectancy is significant ($\beta = 0.061$; $p < 0.05$), thus confirming the views expressed in the Effort Expectancy-System Use Attitude Hypothesis (H13). Also, the total indirect effect of computer-self efficacy on behavioral intentions was positive and significant. However, the total indirect effect of trust in government on attitudes through the role of perceived risk was not significant.

6. Discussion and conclusion

6.1. Outcome of hypotheses

In addition to the seven hypotheses of UMEGA, five other paths were hypothesized to develop the modified version of UMEGA that takes into consideration pertinent factors that have been shown to influence e-government adoption in SSA. The outcomes of the hypotheses are presented in Table 6.

From the thirteen hypotheses, twelve were supported, while one was not. The one hypothesis that failed was the Effort Expectancy-System Use Attitude Hypothesis (H2) which suggested a positive and significant effect of effort expectancy on attitudes. It was also seen that the association between effort expectancy and attitude was non-significant in the original UMEGA tested in the context of this study. This outcome is contrary to evidence from the validation of the original UMEGA by Dwivedi et al. (2017) which showed that effort expectancy was a significant predictor of attitudes towards adoption on e-government services. However, the outcome might not be much of a surprise in the context of SSA, as Lallmahomed et al. (2017) showed that effort expectancy had no significant influence on the behavioral intention to

Table 6
Outcomes of hypotheses.

Hypothesis	Construct link	Std path coef	Critical ratio	Signif (*p*)	Supported?
1	PE → AT	0.33**	4.978	$p < 0.001$	Y
2	EE → AT	−0.05	0.748	$p = 0.455$	N
3	SI → AT	0.14*	2.260	$p = 0.024$	Y
4	FC → BI	0.09*	2.085	$p = 0.037$	Y
5	FC → EE	0.61**	9.425	$p < 0.001$	Y
6	PR → AT	−0.19**	3.371	$p < 0.001$	Y
7	AT → BI	0.74**	13.565	$p < 0.001$	Y
8	CS → AT	0.10*	2.117	$p = 0.034$	Y
9	TG → BI	0.13**	3.653	$p < 0.001$	Y
10	TG → PR	−0.12*	1.992	$p = 0.046$	Y
11	TI → BI	0.08*	2.259	$p = 0.024$	Y
12	EE → PE	0.18*	2.692	$p = 0.007$	Y
13	EE → PE → AT	0.061*	2.456	$p = 0.014$	Y

Note: ** $p < 0.01$; *$p < 0.05$.

adopt e-government services in Mauritius. Similarly, Komba and Ngulube (2015) failed to find a significant influence of perceived ease of use (an equivalence of effort expectancy) on e-government acceptance in Tanzania. Moreover, a growing number of studies around the globe have increasingly questioned the role of effort expectancy in technology adoption as it has shown insignificant associations in numerous contexts (Herero et al., 2017; Morosan and DeFranco, 2016; Oliveira et al., 2016). Even in the validation of the original UMEGA by Dwivedi et al. (2017) effort expectancy showed the smallest effect on attitude when compared to the other variables. This might suggest that as most people are becoming technologically savvy, they are increasingly finding it easy to access e-government websites. Consequently, the degree of ease associated with accessing e-government services is, therefore, playing a minimal role in their attitudes towards using e-government adoption.

With regard to the factors that significantly predict attitudes, it was observed that performance expectancy ($\beta = 0.33$; $p < 0.001$), social influence ($\beta = 0.14$; $p < 0.05$), and computer self-efficacy ($\beta = 0.10$; $p < 0.05$) all had a positive and significant effect on attitudes. These findings supported the Performance Expectancy-System Use Attitude Hypothesis (H1), the Social Influence-System Use Attitude Hypothesis (H3) and the Computer Self-Efficacy-System Use Attitude Hypothesis (H8), respectively. The support for performance expectancy and social influence are in line with the expectations validated in UMEGA (Dwivedi et al., 2017), while the support for computer-self efficacy supports the need for including computer self-efficacy when determining e-government adoption in SSA, as prior studies (Bwalya, 2011; Lallmahomed et al., 2017) have shown this factor to be an important antecedent of e-government acceptance in the region.

Also observed was that perceived risk had a negative and significant direct influence on attitudes towards adoption of e-government services ($\beta = -0.19$; $p < 0.001$). This finding supported the Perceived Risk-System Use Attitude Hypothesis (H6), which is in line with prior studies (Dwivedi et al., 2017; Sulaiman et al., 2012; Susanto and Goodwin, 2011). This shows that when citizens perceive e-government services to be associated with risk, they will be less likely to adopt such services.

In addition to the direct associations with attitudes, there were also several indirect effects that became evident during the hypotheses testing. Dwivedi et al. (2017) proposed in UMEGA that facilitating conditions had a positive association with effort expectancy and this association was also confirmed here in this study ($\beta = 0.61$; $p < 0.001$). As such, the Facilitating Conditions-Effort Expectancy Hypothesis (H5) was supported. The modified UMEGA that is proposed in this study also introduced two indirect effects on attitudes. The first one suggested that effort expectancy had a positive and significant influence on performance expectancy, which was confirmed ($\beta = 0.18$; $p < 0.05$). This supported the Effort Expectancy-Performance Expectancy Hypothesis (H12). Additionally, the Effort Expectancy-System Use Attitude Hypothesis (H13) was also supported, showing that effort expectancy had a significant total indirect effect on the attitudes towards using e-government systems. The outcomes of H12 and H13 are in line with the growing literature on the indirect role of effort expectancy on technology acceptance (Alalwan et al., 2017; Herero et al., 2017; Oliveira et al., 2016). The second one suggested the existence of a significant negative association between trust of government and perceived risk, which was also confirmed ($\beta = -0.12$; $p < 0.05$). This supported the Government Trust-System Risk Hypothesis (*H*10) and is in line with evidence from Belanger and Carter (2008). This indicates that trust of government can play a vital role in minimizing the perceived risk of using e-government services.

Last, it was observed that attitude ($\beta = 0.74$; $p < 0.001$), facilitating conditions ($\beta = 0.09$; $p < 0.05$), trust of government ($\beta = 0.13$; $p < 0.001$) and trust in the Internet ($\beta = 0.08$; $p < 0.05$) all had a positive and significant influence on behavioral intention. This supported the Facilitating Conditions-System Use Attitude Hypothesis (H4), the Individual Attitude-System Use Hypothesis (H7), the

Government Trust-Service Adoption Hypothesis (H9) and the Internet Trust-Service Adoption Hypothesis (*H*11), respectively. The outcomes for H4 and H11 confirmed the validation of the associations in the original UMEGA and are in line with prior studies (Carter et al., 2012; Dwivedi et al., 2017; Hung et al., 2013; Lallmahomed et al., 2017; Lu et al., 2010).

6.2. Implications for practice

This study showed that attitude was the most decisive factor in explaining the behavioral intention to adopt e-government services in South Africa. This supports the growing literature that has increasingly shown that shaping users' attitudes can significantly influence their acceptance of e-government services (Dwivedi et al., 2017; Hung et al., 2013; Lu et al., 2010). It is, therefore, imperative for the different government departments offering e-government services to find ways of developing positive e-government related attitudes in citizens.

One possible means through which individuals' attitudes towards e-government can be shaped is through training programs (Dwivedi et al., 2017). When users become trained in using e-government systems, they will be more likely to develop a positive attitude towards using the systems. This is also supported in this study by the positive influence of computer self-efficacy on attitudes, clearly indicating that users will be more likely to have a positive attitude towards e-government systems if they believe they have the technical competencies to use such systems. Such training is particularly important for people with low literacy rates, as Mukhongo (2015) highlighted that even though some SSA countries like Kenya, Nigeria, and South Africa provided free Internet access during promotion hours, many people in these countries were still unable to use the Internet due to low literacy rates. The study, therefore, supports the numerous calls by researchers for the need to provide ordinary citizens with training on how to use e-government websites and access the available e-services (Alawadhi and Morris, 2009; Bhuasiri et al., 2016).

The other factors that were found to significantly influence user attitudes are performance expectancy, social influence, and perceived risk. Performance expectancy focuses on the usefulness of e-government services. It was seen that citizens will be more likely to have a positive attitude in accessing e-government services that are deemed to be useful. As such, government agencies can focus on public campaigns that emphasize the usefulness of e-government websites and how accessing e-government services could benefit citizens.

However, while focusing on the usefulness of the e-government websites, it is also imperative for designers and developers of these systems to make them easy to use. This is because even though effort expectancy (perceived ease of use) will not directly change attitudes towards e-government service, it is a significant antecedent of performance expectancy (as shown in H12) which had the highest influence on shaping attitudes. Moreover, the total indirect effect of effort expectancy on attitudes was significant (as shown in H13). This implies that even though a useful e-government system will stir up positive attitudes towards it, making the system useful and easy to use will possibly increase the citizen's interest in it more than if the system was useful but difficult to use. E-government system designers and developers in South Africa can adopt a user-centered design approach as a means of creating e-government systems that are both useful and easy to use.

Also, the positive effect of social influence on attitudes suggests that citizens will easily develop positive attitudes towards e-government services if such services were supported by their significant others (e.g. family members, friends, and colleagues). As such, government agencies can start by encouraging their employees to recommend e-government services to their close networks as they will then, in turn, recommend it to others until it reaches critical mass (Lallmahomed et al., 2017). Also, governments can leverage the power of social media to promote e-government services. Social media is a key tool in the power of social influence and can be used to promote the use of a new technology (Oliveira et al., 2016).

The negative influence of perceived risk on attitudes is also a factor that should be considered by government agencies. Research has shown that over 80% of Internet users are skeptical about providing their personal information on the Internet (Rana et al., 2015). As such, governments need to promote information about the security and privacy measures being put in place to protect citizens who are accessing e-government services. This is particularly important as recent evidence suggested that most websites in SSA, including South African government websites, performed poorly in aspects of security and privacy (Verkijika, 2017). Also, by assuring citizens that those e-government systems will meet their security and privacy concerns, governments will be gaining the trust of the users in addition to minimizing risk perceptions. This is important as both trust of the Internet and trust of government are significant predictions of the behavioral intention to adopt e-government services. For transactional e-government services, strong authentication mechanisms should be put in place. Furthermore, governments should show a strong commitment to the implementation of e-government services and present a positive image regarding such services, as the credibility of the government is central in gaining citizen's trust (Belanger and Carter, 2008).

Last, facilitating conditions showed a significant positive influence on behavioral intention. With respect to facilitating conditions, one of the key aspects that the government in South Africa can consider is the provision of free Internet access to facilitate user access to e-government services. Several governments around the world have also adopted such an approach, such as in Qatar (Al-Shafi and Weerakkody, 2011) and Egypt (OECD, 2013). It is, however, encouraging to see that some of such efforts are being rolled out in South Africa. For example, the South African government could provide support to non-profit organizations, like Project ISIZWE that focuses on providing free public Wi-Fi in poor communities around the country.

6.3. Implications for theory

Research over the years has established the need to test technology adoption models in different countries in order to ascertain its applicability, while also looking for relevant factors to expand it (Dwivedi et al., 2017; Oliveira et al., 2016). In the context of e-government studies, Dwivedi et al. (2017) recently developed and validated UMEGA in the Indian context. UMEGA was developed from nine well known theoretical models and its validation showed that it outperformed all the other models. However, to the best of our knowledge, UMEGA has not been validated in other contexts. This study, therefore, served as a second validation of UMEGA from a different context. It was observed that UMEGA (R^2 of 64.7%) outperformed other models in SSA in predicting behavioral intention, such as the combination of UTAUT2 and GAM by Lallmahomed et al. (2017) in Mauritius (R^2 of 38%). But the universality of all the associations proposed by UMEGA was questioned in the SSA context. This was because effort expectancy failed to predict attitudes as expected. In addition, Lallmahomed et al. (2017) had shown in their model that effort expectancy also failed to predict behavioral intention in e-government adoption in Mauritius. Nevertheless, this study showed that effort expectancy instead had an indirect effect on attitudes, via the mediating role of performance expectancy. This suggests a need for refining the associations in individual technology acceptance models for better insight in its applicability in a different context.

Also, this study used factors such as computer self-efficacy and trust, which have been shown to be valuable in e-government adoption in SSA, but not considered in UMEGA as a basis for extending the model. It was observed that by extending the model with these two factors, the explanatory power of attitudes increased by 3.2% while that for behavioral intention improved by 4.5%. For researchers, this study indicates that even though UMEGA is well grounded and outperforms similar models, it can still benefit from further theoretical refinement while keeping the model parsimonious and simple to implement.

6.4. Limitations

As with most research studies, the findings of this study should be read in line with the associated limitations as they provide the impetus for further research. This study has two key limitations. The first limitation relates to the fact that data were collected only from South Africa. As such, this limits the generalizability of the findings to the context of SSA. Moreover, it is possible that some sections of the population might have been over- or under-represented in the sample due to the convenience sampling approach. This also limits the generalizability of findings. Nonetheless, this creates an avenue for future studies in SSA, as the goal of this study was to propose a modified version of UMEGA model that could be tested across different countries in SSA to better ascertain the factors that influence e-government adoption in the region.

The second limitation relates to the factors used to modify UMEGA. The factors (computer self-efficacy and trust) were based on extant empirical evidence from SSA. However, given the limitations in the current e-government adoption from SSA and the over-emphasis on TAM by these studies, it is possible that there are other factors that could also be appropriate for extending UMEGA. As such, future studies can increase the extensiveness of the literature review to identify other factors that could be used to modify UMEGA in the context of SSA. One important area will be to examine factors that could improve the explanatory power of attitudes towards e-government. The total variance explained for attitudes both in the original UMEGA by Dwivedi et al. (2017) and is this study is still low (below 50%). Thus the models can benefit from the inclusion of other predictor variables of attitudes. While making these improvements, future studies should consider the trade-off between model complexity and explanatory power to ensure that the modified model remains parsimonious and simple to implement.

The study contributes to the current literature on e-government development, especially by providing new insights from an SSA context, with empirical evidence from South Africa. Over the years, most of the e-government adoption studies from SSA have mainly focused on TAM (Asianzu and Maiga, 2012; Bwalya, 2011; Khanyako and Maiga, 2013; Lin et al., 2011; Rukiza et al., 2011). Only recently did SSA researchers start validating other models such as UTAUT2 and GAM (Lallmahomed et al., 2017). UMEGA was recently developed and validated as an e-government specific model that outperformed others in understanding e-government acceptance. This study adopted and validated UMEGA with data from South Africa. The findings showed that all the proposed associations of UMEGA were significant, except for the association between effort expectancy and attitude. This study further extended UMEGA with computer self-efficacy and trust and found that the modified model performed better in the South African context than the original UMEGA, both in predicting attitudes and behavioral intention.

Appendix A

Survey items

Constructs and Items

Attitude (AT)
- AT1 - Using e-government services would be a good idea.
- AT2 - Using e-government services would be a wise idea.
- AT3 - I like the idea of using e-government services.
- AT4 - Using e-government services would be pleasant.

Behavioral intention (BI)
- BI1 - I intend to use e-government services in the future.
- BI2 - I predict I would use e-government services in the future.
- BI3 - I plan to use e-government services in the future.

Computer self-efficacy (CS)
- CS1 - I am confident in my ability to use e-government services
- CS2 - I have the necessary skills to use the e-government services.
- CS3 - I have the necessary qualifications to use e-government services.

Effort expectancy (EE)
- EE1 - My interaction with e-government services would be clear and understandable.
- EE2 - I would find e-government services easy to use.
- EE3 - It would be easy for me to become skillful at using e-government services.
- EE4 - Learning to operate e-government services would be easy for me.

Facilitating conditions (FC)
- FC1 - I have the necessary resources to use e-government services.
- FC2 - I have the necessary knowledge to use e-government services.
- FC3 - I can get help from others when I have difficulties using e-government services.

Perceived Risk (PR)
- PR1 - Use of e-government services may cause my personal information to be stolen.
- PR2 - I would feel uneasy psychologically if I used e-government services.
- PR3 - I think that it is unsafe to use e-government services because of the privacy and security concerns.
- PR4 - I believe that there could be negative consequences from using e-government services.

Performance expectancy (PE)
- PE1 - Using e-government services will help me to accomplish things more quickly.
- PE2 - I would find e-government services useful in daily life.
- PE3 - Using e-government services will make my life easier.

Social influence (SI)
- SI1 - People who are important to me think I should use e-government services.
- SI2 - People whose opinions I value would prefer me to use e-government services.
- SI3 - People who influence me think that I should use e-government services.

Trust of government (TG)
- TG1 - I think I can trust government agencies to carry out online transactions faithfully.
- TG2 - I trust that government agencies keep my best interests in mind.

Trust in the Internet (TI)
- TI1 - The Internet has enough safeguards to make me feel comfortable using it to access e-government services.
- TI2 - I feel assured that legal and technological structures adequately protect me from problems on the Internet.
- TI3 - In general, the Internet is now a robust and safe environment to transact using e-government services.

Appendix B

Item loadings (bold values) and cross-loadings

Items	AT	BI	CS	EE	FC	PR	PE	SI	TG	TI
AT1	**0.751**	0.474	−0.096	0.056	0.182	−0.109	0.389	0.086	0.103	0.072
AT2	**0.879**	0.503	−0.019	0.032	0.090	−0.179	0.223	0.154	0.194	0.148
AT3	**0.900**	0.548	−0.021	0.069	0.150	−0.230	0.265	0.180	0.207	0.228
AT4	**0.887**	0.417	-0.008	0.054	0.219	−0.088	0.420	0.227	0.177	0.026
BI1	0.471	**0.724**	−0.158	0.158	0.249	−0.094	0.596	0.182	0.221	0.087
BI2	0.597	**0.873**	−0.001	0.098	0.165	−0.205	0.313	0.238	0.288	0.203
BI3	0.642	**0.889**	−0.031	0.094	0.190	−0.258	0.311	0.230	0.256	0.272
CS1	−0.038	−0.066	**0.994**	−0.026	−0.035	0.055	−0.190	−0.157	−0.006	−0.051
CS2	−0.032	−0.059	**0.993**	−0.046	−0.041	0.048	−0.205	−0.152	0.002	−0.048
CS3	−0.006	−0.060	**0.947**	−0.087	−0.075	0.018	−0.206	−0.159	0.002	−0.012
EE1	0.084	0.128	−0.029	**0.954**	0.582	−0.113	0.170	0.247	0.138	0.071
EE2	0.056	0.109	−0.027	**0.965**	0.585	−0.117	0.158	0.243	0.155	0.081
EE3	0.024	0.095	−0.033	**0.919**	0.530	−0.159	0.124	0.236	0.104	0.119
EE4	0.070	0.171	−0.059	**0.902**	0.567	−0.074	0.216	0.252	0.158	0.032
FC1	0.161	0.232	−0.053	0.538	**0.943**	−0.118	0.416	0.246	0.211	0.084
FC2	0.145	0.206	−0.037	0.552	**0.918**	−0.080	0.434	0.201	0.149	0.055
FC3	0.066	0.185	−0.047	0.540	**0.789**	−0.028	0.285	0.362	0.163	0.006
PR1	−0.239	−0.241	0.001	−0.099	−0.120	**0.947**	−0.095	−0.094	−0.112	−0.833
PR2	−0.215	−0.209	0.032	−0.115	−0.093	**0.961**	−0.055	−0.077	−0.109	−0.903
PR3	−0.188	−0.207	0.095	−0.134	−0.083	**0.957**	−0.090	−0.055	−0.115	−0.864
PR4	−0.164	−0.243	0.072	−0.114	−0.027	**0.883**	−0.078	−0.079	−0.125	−0.878
PE1	0.273	0.317	−0.138	0.126	0.316	−0.119	**0.728**	0.082	0.120	0.106
PE2	0.184	0.277	−0.234	0.124	0.278	−0.062	**0.735**	0.104	0.157	0.044
PE3	0.314	0.463	−0.173	0.121	0.341	−0.019	**0.878**	0.158	0.128	−0.010
SI1	0.110	0.185	−0.122	0.218	0.225	−0.102	0.060	**0.880**	0.115	0.075
SI2	0.155	0.276	−0.127	0.292	0.344	−0.089	0.214	**0.808**	0.138	0.087
SI3	0.172	0.212	−0.146	0.164	0.179	−0.032	0.089	**0.875**	0.083	0.013
TG1	0.173	0.267	−0.031	0.141	0.194	−0.149	0.183	0.143	**0.920**	0.145
TG2	0.198	0.292	0.068	0.147	0.183	−0.122	0.141	0.102	**0.909**	0.125
TI1	0.200	0.249	−0.072	0.084	0.055	−0.919	0.063	0.080	0.128	**0.987**
TI2	0.176	0.229	−0.019	0.073	0.041	−0.904	0.055	0.046	0.110	**0.984**
TI3	0.216	0.315	−0.043	0.128	0.175	−0.072	0.155	0.119	0.069	**0.986**

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