Fostering the Adoption of Smart E-Government Services in Germany

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Abstract

Governments worldwide recognize a need to provide services online to their citizens. Increasingly, these services have become sophisticated through the application of advanced technologies. Nevertheless, the adoption of such services often lags behind expectations. Thus, this study proposes and tests an extension of the unified model of electronic government adoption (UMEGA) to the context of smart e-government services in Germany. It was empirically tested using the data of 330 respondents. The adapted model greatly exceeds other studies that applied an adapted UMEGA regarding the explanatory power on attitude, while the study proves that resistance to change in the investigated context unfolds a highly significant impact on behavioral intention compared to other findings. Concluding, the proposed model supports governments in planning smart e-government services and corresponding strategies more holistically by understanding the factors that influence citizens' adoption.

Keywords

Adoption, UMEGA, e-government, smart services, e-government services, smart e-government.

Introduction

In the past two decades, the use of digital services such as banking (Chavan 2013), e-commerce (Nayak et al. 2021), and learning platforms (Jethro et al. 2012) have become an integral part of modern life. Digital services offer convenient access, time-saving processes, cost-effectiveness, and to some extent, customizations on the user and provider side (Chavan 2013). Recently, the introduction of smart digital services increased. While through digital services, user benefit from online availability, smart digital services use advanced technologies to deliver personalized and contextualized experiences (Criado and Gil-Garcia 2019). Commonly known are chatbots that apply artificial intelligence (AI) to understand user input, interpret their intent, and generate appropriate responses (Kumar and Ali 2020).

Within the public sector, authorities recognized the need to introduce digital government services (e.g., digital identity systems, e-voting systems), which are becoming essential for modern government operations. Thus, we define smart e-government services (SEGS) as those accessible using mobile technologies, advanced by intelligent technologies, and offered by the government (Gascó-Hernandez

2018). They can provide many benefits to citizens, including convenience, efficiency, cost-effectiveness, transparency, and accessibility, by allowing citizens to submit forms and applications more conveniently. While digital government services include the same benefits as commercial digital services, they also positively impact administration by streamlining operations and reducing bureaucracy (Criado and Gil-Garcia 2019). In the past, Germany has continued to develop its government services, focusing on improving efficiency, digitalization, and accessibility, e.g., by launching the “Online Access Act,” which requires federal authorities to make their services digitally available (Federal Ministry of the Interior, Building and Community 2019). Nonetheless, Germany struggles to gain acceptance of such services by citizens despite the potential of SEGS to increase not only efficiency but also transparency and traceability for users through the application of intelligent technologies. Germany thus lags in implementing e-services successfully compared to other European countries (European Commission 2020).

While the underlying problem landscape for the slow proliferation of SES is bound to be complex and multifaceted, in this paper, we will focus on the citizen side of the issue. Here, we believe that increasing knowledge on citizens’ acceptance criteria can help foster the proliferation of more sophisticated SEGS. To our knowledge, no studies have yet investigated this aspect, however. We thus propose the following research question: *Which factors influence the citizens' adoption of SEGS?*

To answer this question, this study investigates the adoption of SEGS in Germany by deriving and testing hypotheses based on an expanded Unified Model of E-Government Adoption (UMEGA) (Dwivedi et al., 2017). The study focuses on identifying the factors that may positively or negatively impact the endorsement of SEGS by citizens. A quantitative-empirical approach is adopted to test the hypotheses, with a sample size of 330 citizens. The paper thus contributes key factors that foster citizens’ adoption of SEGS in Germany. These factors will become increasingly relevant in the future as the application of advanced technologies in SEGS becomes increasingly integral, and SEGS become ever more pervasive in Germany and other countries.

Conceptual Model and Hypothesis Development

Significant progress has been made in developing e-government services and e-participation systems, resulting in various public services now delivered online with many benefits for citizens. In addition to digitalization, a continued focus is improving efficiency and streamlining processes through smartification. SEGS can adapt to citizens' behavior, preferences, and needs and provide real-time feedback and insights to improve citizens' experiences (Kumar and Ali 2020). They rely on the collection, processing, and analysis of vast amounts of data to generate actionable insights and enable automated decision-making. Examples of SEGS include virtual assistants, chatbots, or predictive analytics tools. The concept of SEGS thus embraces innovative approaches to public service delivery. It leverages digital infrastructures to improve political efficiency, economy, and social well-being while strengthening the ambition of agility and resilience (Velsberg et al. 2020). However, applying advanced technologies for SEGS can be more challenging than in the private sector because it involves policy decisions and often addresses complex social problems (Gascó-Hernandez 2018). Velsberg et al. (2020) emphasize that it takes human readiness and willingness to deploy smart services in the public sector. Implementing new and innovative technologies is not a precondition for successful e-government. Despite the numerous initiatives investigating the application of quality management principles to delivering SEGS, manifold problems related to the quality of public e-services still exist. Unable to find the needed service or information, difficult use of e-services, the need for better help regarding the e-service provided on the website, the language understandability, etc., are some of the frequently reported usability problems.

Performance Expectancy (PE): PE is defined as the extent to which an individual believes that using the system will help to achieve an improvement in work performance (Venkatesh et al. 2003) or in completing a particular task (Venkatesh et al. 2012). SEGS enable improved processes within the administration and regarding citizens. A citizen's attitude can be determined by the extent to which the e-government system is useful and beneficial (Dwivedi et al. 2017). Thus, online government service only occurs when citizens can identify added value. In past studies based on the UMEGA, PE significantly impacted attitude (e.g., Avazov and Lee 2022; Dwivedi et al. 2017; Rana et al. 2017; Verkijika and Wet 2018). The findings indicate PE influences a citizen’s attitude toward using such online governmental systems. We assume the same for sophisticated SEGS: *H1: Performance expectancy positively impacts the intention to use SEGS.*

Effort Expectancy (EE): Venkatesh et al. (2003) consider EE the degree of simplicity associated with using the system. The consolidation of national registers, the implementation of the principle of recording personal data only once for citizens and companies, and thus the pre-filling of forms with data available facilitate the use of administrative systems. Online processes that are consistently maintained can facilitate citizen-friendly application operations by eliminating media breaks. Several studies showed that EE has a significant impact on citizen attitudes. This has been studied in the context of online tax filing systems (Lu et al. 2010) and mobile e-government services (Hung et al. 2013). The easier a technology is to use, the more positive the attitude toward e-government services and the more inclined citizens are to adopt it (e.g., Avazov and Lee 2022; Dwivedi et al. 2017; Rana et al. 2017). Therefore, we state the following hypothesis: *H2: Effort expectancy has a positive impact on the intention to use SEGS.*

Social Influence (SI): Social influence refers to the extent to which an individual perceives that others believe in using the new system (Venkatesh et al. 2003). As a result, individuals are inclined to adopt a particular system if family, friends, and colleagues endorse its use (Venkatesh et al. 2012). Research findings on social influence on the adoption of e-government services are mixed. Although studies have shown that social influence does not affect attitudes (Avazov and Lee 2022; Mensah et al. 2020), other studies have found that social influence positively relates to citizens' attitudes (Dwivedi et al. 2017; Rana et al. 2017; Verkijika and Wet 2018) and their intention to adopt e-government services (Kurfalı et al. 2017; Zuiderwijk et al. 2015). This suggests that citizens develop positive attitudes toward SEGS when these services are supported by their key caregivers: *H3: Social influence has a positive impact on the intention to use SEGS.*

Facilitating Conditions (FC): Facilitating conditions are defined as the extent to which an individual believes that an organizational and technical infrastructure is in place to support the use of the system, thereby removing barriers to use. In developing UTAUT, Venkatesh et al. (2003) argued that facilitating conditions impact technology adoption in the organizational context, while Venkatesh et al. (2012) extend this to the consumer context. Various studies have shown that facilitating conditions significantly influence citizens' intention to adopt e-government systems (Alshehri et al. 2013; Kurfalı et al. 2017; Lallmahomed et al. 2017; Rana et al. 2016). A relationship between facilitating conditions and intention to use was also found in the more advanced UMEGA (Avazov and Lee 2022; Dwivedi et al. 2017; Rana et al. 2017; Verkijika and Wet 2018). In analyzing e-file use among U.S. taxpayers, e.g., facilitating conditions significantly influenced intent to use e-files (Carter et al. 2012; Schaupp et al. 2010). For SEGS, facilitating conditions represent the degree to which citizens believe that sufficient resources are available to enable the use and access: *H4: Facilitating conditions have a positive impact on the intention to use SEGS.*

UMEGA further posits that facilitating conditions also indirectly affect attitudes toward e-government through their influence on effort expectation (Dwivedi et al. 2017; Mensah et al. 2020; Verkijika and Wet 2018). Good quality technical infrastructure and support from the relevant government agencies can influence access to and use of SEGS. Providing necessary resources and training helps citizens to understand and use the system more easily (Dwivedi et al. 2017). Accordingly, if citizens are confident that the necessary facilitating conditions are in place, this improves not only their intention to use but also their understanding of the effort expectation of SEGS. *H5: Facilitating conditions have a positive impact on the intention to use SEGS.*

Perceived Risk (PR): IT risk refers to the likelihood that a system is inadequately protected against various forms of damage (Straub and Welke 1998). A citizen’s perceived risk is thus considered an individual perception or subjective assessment of suffering loss or harm when experimenting or interacting with new technologies or innovations (Mensah et al. 2020; Warkentin et al. 2002). Findings demonstrate that risk perceptions are a significant barrier to using e-services (Rana et al. 2015; Schaupp et al. 2010). This belief is specially held for e-government services accessible via the Internet (Verkijika and Wet 2018). The perceived risk significantly influences attitudes toward using these technological systems, such that citizens with high-risk perceptions are less likely to use e-government solutions (Dwivedi et al. 2017; Mensah et al. 2020; Verkijika and Wet 2018). As smart government increases its focus on linking and analyzing generated data, there are increased privacy concerns among citizens. When citizens feel that the risk of using SEGS is high, they become discouraged or have a negative attitude toward adopting SEGS: *H6: Perceived risk has a negative impact on the intention to use SEGS.*

Attitude (ATT): Attitude towards technology adoption is the extent to which an individual user makes either a positive or negative evaluation of using or interacting with technology (Ajzen 1980; Dwivedi et al.

2017). Models and theories of acceptance research, such as UTAUT, do not consider variable attitude. Instead, they point to a direct effect of perceived usefulness, perceived ease of use (e.g., Avazov and Lee 2022), performance expectancy, effort expectancy, social influence, and facilitating conditions on intention to use (Venkatesh et al. 2003). Dwivedi et al. (2017) increased the explanatory power tremendously compared to UTAUT by introducing attitude as a mediating variable. In contrast to the original models, this additional construct is very important as e-government systems in the context of Germany are citizen-centered and voluntary (Dwivedi et al. 2017). Citizens who positively view an SEGS are more inclined to adopt it and vice versa. The relationship between attitude and behavioral intention has been validated in several e-government studies (e.g., Avazov and Lee 2022; Hung et al. 2009; Lu et al. 2010). In analyzing citizen adoption of mobile e-government services in Taiwan, Hung et al. (2013) found that attitude is a critical factor in understanding and predicting mobile citizens' behavioral intentions.

Behavioral Intention (BI): Behavioral intention to use is assumed to influence the actual use of new technologies. In many studies, the relationship between intention to use and actual use is well established, so both variables can be used to measure technology acceptance (Davis et al. 1989; Taylor and Todd 1995; Venkatesh et al. 2003). In the context of smart government, citizens with a positive attitude or evaluation of the services intend to use a SEGS: *H7: Attitude has a positive impact on the intention to use SEGS.*

Trust in Government (TiG): Carter and Bélanger (2005) suggest that perceptions of trustworthiness influence citizens' intentions towards e-government services. But trust must be considered from different perspectives to fit the specific context. Trustworthiness is defined as the perception of trust in the reliability and integrity of the electronic marketer Trust in e-government is thus composed of trust in a particular entity providing a service (Bélanger and Carter 2008; Zhao and Khan 2013). Building strong trust on the part of citizens is imperative for e-services to be adopted and e-government to be successful Trust in government refers to the perception of the integrity and capability of the agency providing the service (Bélanger and Carter 2008). Past studies have also shown that trust in government has a positive and significant direct impact on behavioral intention to use e-government services (Abu-Shanab 2017; Lallmahomed et al. 2017). Before citizens can have confidence in SEGS, they must be convinced that the government agency has the foresight, management, and technical resources needed to successfully implement SEGS: *H8: Trust in government has a positive impact on the intention to use SEGS.*

Trust in the Internet (TiI): Trust in the Internet is repeatedly identified as a significant factor influencing the acceptance of e-services (Carter and Bélanger 2005; Warkentin et al. 2002). This type of trust is often referred to as institution-based trust. It is defined as the perception of the institutional environment, including the structures and rules that make an environment appear safe. Previous studies confirm the positive and significant relationship between trust in the Internet and behavioral intention to use e-government services (Bélanger and Carter 2008; Kurfalı et al. 2017; Verkijika and Wet 2018). Whether SEGS are adopted depends on the extent to which citizens believe that the Internet is a reliable technology capable of providing accurate information and conducting secure transactions: *H9: Trust in the Internet has a positive impact on the intention to use SEGS.*

Resistance to change (RtC): The construct RtC is another reason for the discrepancy between the e-government services offered and the low adoption of the services. This affects the introduction of e-government services and leads to the failure of new IS systems (Dwivedi et al. 2015). In the context of e-government, RtC has not been sufficiently studied. A study in Mauritius found that RtC hinders e-government adoption (Shalini 2009). Some citizens prefer to stay in the current situation, the status quo, or to avoid and resist this situation. Negative consequences that may be perceived with the change could also be a reason for resistance. IS literature describes RtC as a negative reaction that citizens show to the proposed change (Hirschheim and Newman 1988; Kim and Kankanhalli 2009). For this reason, citizens' resistance to e-government services negatively affects their intention to use these services (Lallmahomed et al. 2017). In terms of smart government, this means that citizens resist switching from traditional government services to adopting newly implemented SEGS: *H10: Resistance to change has a negative impact on the intention to use SEGS.*

The adoption of e-government services is based on the belief that government agencies have the necessary resources to implement electronic services effectively and, at the same time, that the Internet as the medium used can provide adequate safeguards against risks (Bélanger and Carter 2008). Particularly at the beginning of the implementation of such services, citizens will show resistance as they are not yet familiar with the e-government concept (Abu-Shanab 2014). Lack of trust in the government and the technology used therefore leads to increased resistance to the introduction of e-government services. Accordingly, as trust increases, citizens' resistance to using e-government services decreases (Lallmahomed et al. 2017). When citizens build trust in the government and the internet, they are more open toward new SEGS. Accordingly, they may be more willing to change their current behaviors and test SEGS. Thus, the UMEGA was adapted, and TiI, TiG, and RtC were added to the model: *H11: Trust in the Internet has a negative impact on resistance to change to use SEGS. H12: Trust in government has a negative impact on resistance to change to use SEGS.*

In addition, research shows that EE has a significant negative relationship with RtC. In the context of a digital library system, it was shown that high RtC would mean that citizens would have to expend more effort to learn and use the technology (Nov and Ye 2009). Another study found that the ease of use of an e-government system minimizes resistance to adopting such services. Citizens may perceive that an extensive effort is required to learn how to use and utilize this system, which may contribute to RtC. Similarly, citizens with little effort in operating such a system would experience less RtC (Lallmahomed et al. 2017). Citizens are more likely to trade traditional government services for SEGS if they can be operated and navigated in a user-friendly manner: *H13: Effort expectancy has a negative impact on resistance to change to use SEGS.*

Research Method and Process

First, we reviewed existing models that focused on the adoption of technology and e-government services, covering various geographical regions. Second, we substantiated our hypothesis with existing findings generated through search and analyses in established databases (i.e., ACM Digital Library, ScienceDirect). We applied a quantitative-empirical approach to test our hypothesis. Conducting a survey as a quantitative method seems rigorous to answer our research question and provide results of high generalizability (Johnson 2000). We used established measurement constructs, translated them, and adapted them in wording and language to our context. Since validated scales already covered our research objective, we solely relied on existing measurement scales. The items for PE, EE, SI, FC, PR, ATT, and BI were adapted from Venkatesh et al. (2003), Mensah et al. (2020), Dwivedi et al. (2017), Verkijika and Wet (2018), Weerakkody et al. (2013). For measuring TiG and TiI, we used scales from Verkijika and Wet (2018), Carter and Bélanger (2005), and Weerakkody et al. (2013). The items of RtC were obtained from the study of Lallmahomed et al. (2017). Before collecting our large-scale data, we checked the constructs' content validity by performing card-sorting procedures according to Moore and Benbasat (1991), gaining a hit ratio of 98.41%. After minor changes, we conducted a pre-test, showing no need for action. We conducted the study with German residents and provided the questionnaire in German language for comprehensibility reasons. Data was gathered by spreading the self-administered questionnaire online across various social media channels and forums. The data collection was carried out in 2021 and lasted four weeks. We presented all study participants a definition of SEGS and a differentiation from e-government services. Further, we provided three examples of SEGS including an informative description to provide a consistent understanding of the main attributes of the study among participants. After the cleaning of our data sets, we considered a total of 330 responses for further analysis. More female (61.5%) than male respondents (38.5%) took part in the study. In general, all age groups between 18 and 87 years old are represented, with an average age of about 34 years. This is about 10 years younger than the average age in Germany at that time (Federal Institute for Population Research, 2021). In addition, most participants were between 25 and 26 years old (23.6%) and more than a third were studying (37.3%). In terms of current job situation, according to students, most are employed in the private sector (30.6%) or in the public sector (16.1%). Regarding the number of inhabitants of the place of residence, more than half of the participants live in a large city (51.8%), while the distribution of the other options was relatively balanced. More than 40% of respondents use the internet more than four hours per day. Almost half of the respondents had already had experience with a government online service (48.5 %), of whom more than 60 % were rather satisfied or even completely satisfied. Nevertheless, almost 25% of the participants were rather dissatisfied or not at all satisfied.

Findings

Assessment of the Measurement Model: We tested our measurement model for internal consistency, indicator reliability, convergent validity, and discriminant validity. To test for internal consistency, we checked Cronbach's alpha (CA) and composite reliability (CR), and the data met the threshold of 0.7 (Hair et al. 2019) (cf. Table 1). Nevertheless, the construct BI shows a reliability higher than 0.95. This may indicate a possible bias, i.e., that all indicators measure the same. Since the construct consists of only three items and a test with fewer items would cloud the meaningfulness of the construct measurement, as well as the elimination of individual items would not have led to reliability below 0.95, we refrained from elimination. We assessed convergent validity by calculating the average variance extracted (AVE) and met the threshold of at least 0.5 (Fornell and Larcker 1981) (cf. Table 1). Factor loadings were measured for reflective constructs (i.e., FC). Only FC_3 did not meet the threshold of 0.708, while containing a value between 0.40 and 0.70, an item should only be removed if reliability (CA and/or CR) is too low and the threshold is exceeded by an elimination (Hair et al. 2019). For this reason, all items remain part of the evaluation. Further, we checked the measurement model for discriminant validity based on cross-loadings (Chin 2013; Urbach and Ahlemann 2010), the Fornell-Larcker criterion (Fornell and Larcker 1981), and the heterotrait-monotrait ratio (HTMT, Henseler et al. 2015). When analyzing the evaluated data, it can be seen that the values of the items FC_3 and ATT_4 are critical. The value of FC_3 (0.537) is slightly lower than the items EE_3 (0.604) and EE_4 (0.556) within the construct effort expectancy. Furthermore, the value of item ATT_4 (0.804) is slightly lower than that of intention to use (BI_1 = 0.850; BI_2 = 0.828; BI_3 = 0.833). Since discriminant validity will be examined below using additional criteria, these values are not an exclusion criterion for further data analysis. Regarding the Fornell-Larcker criterion, the analyzed data show that all constructs in this study share more variance with their associated indicators than any other construct (Hair et al. 2019).

Construct	Items	CA	CR	AVE
Performance Expectancy (PE)	5	0.905	0.929	0.725
Effort Expectancy (EE)	5	0.934	0.950	0.791
Social Influence (SI)	5	0.910	0.933	0.737
Facilitating Conditions (FC)	4	0.807	0.874	0.642
Perceived Risk (PR)	5	0.913	0.934	0.738
Trust in Government (TiG)	5	0.914	0.935	0.742
Trust in the Internet (TiI)	4	0.908	0.935	0.783
Resistance to Change (RtC)	3	0.921	0.950	0.864
Attitude (ATT)	5	0.926	0.945	0.774
Behavioral Intention (BI)	3	0.964	0.976	0.932

Table 1. Assessment of Convergent Validity and Internal Consistency Reliability

Assessment of the Structural Model: We checked our model for collinearity issues by calculating the variance inflation factor (VIF). The results showed that all VIF values were below 5 (Hair et al. 2019), indicating no collinearity issues exist. As suggested by Hair et al. (2016), we begin evaluating the inner model regarding the structural model's explanatory power. Thus, we checked the R^2 values and the effect sizes (f^2). For our dependent variable BI, the R^2 is 0.773. Chin (2013) estimates values of about 0.670 to be substantial, meaning to contain high explanatory power. The f^2 values indicate that a large effect is present for the relationships ATT→BI (0.759), FC→EE (0.549), PE→ATT (0.493), a medium effect for the relationship EE→RtC (0.177), and a small effect for the relationships PR→ATT (0.116), RtC→BI (0.061), TII→RtC (0.051), and EE→ATT (0.046). The other five relations (SI→ATT, TIG→RtC, FC→BI, TII→BI, TIG→BI) show no effects because $f2 < 0.02$. Using the blind folding and Q2 value, the predictive relevance of the path model can be determined for each endogenous construct. The higher Q2 is, the higher the predictive relevance of the variable (Urbach and Ahlemann 2010). Since all values exceed 0, the predictive relevance of the model is supported for all endogenous variables (Hair et al. 2019). Intention to use BI (Q2 = 0.713) has the highest Q2 value, followed by attitude ATT (Q2 = 0.489), resistance to change RtC (Q2 = 0.287), and effort expectancy EE (Q2 = 0.275).

Hypothesis	Path coefficient	t-value	f^2-value
H1: PE -> ATT	0.550***	9.685	0.493
H2: EE -> ATT	0.155*	2.425	0.046
H3: SI -> ATT	0.086**	2.656	0.018

H4: FC -> BI	0.055	1.477	0.009
H5: FC -> EE	0.596***	12.403	0.549
H6: PR -> ATT	-0.225***	5.275	0.116
H7: ATT -> BI	0.0683***	11.658	0.759
H8: TiG -> BI	0.016	0.364	0.001
H9: TiI ->BI	0.052	1.410	0.007
H10: RtC -> BI	-0.166***	3.649	0.061
H11: TiI -> RtC	-0.233***	3.963	0.051
H12: TiG -> RtC	-0.133*	2.103	0.017
H13: EE -> RtC	-0.370***	6.639	0.177
R^2(BI): 0.773	R^2(EE): 0.355	**Note**: * p = <0.050; ** p = <0.010; *** p = <0.001	
R^2(ATT): 0.643	R^2(RtC): 0.336		

Table 2. Hypothesis Testing

Discussion and Conclusion

Our analysis reveals a direct and positive effect between PE (H1), EE (H2), SI (H3), and ATT to use SEGS, while PR (H6) shows a direct negative effect on ATT. Further, ATT (H7) shows a positive effect on BI, whereas RtC (H10) shows a negative effect on BI. TiI (H11), TiG (H12), and EE (H13) all reveal direct negative effects on RtC. Last, FC (H5) show a direct positive effect on EE. In contrast, FC (H4), TiG (H8), and TiI (H9) on BI are not statistically significant in our results. Compared to previous studies on adopting e-government services (e.g., Dwivedi et al. 2017; Verkijika and Wet 2018), PE shows a stronger relationship and higher significance on ATT in the context of SEGS in Germany. This could be associated with the advanced functionalities citizens expect from applying sophisticated technologies such as AI and IoT. Further, our outcome supports findings by, e.g., Avazov and Lee (2022) and Almaiah and Nasereddin (2020), who showed that EE was a significant predictor of ATT towards adopting e-government services. Although citizens are becoming more technology knowledgeable and studies found contrary outcomes (e.g., Oliveira et al. 2016), the effort remains significant regarding sophisticated SEGS.

The relationship between SI on ATT validated the research of Dwivedi et al. (2015) and Rana et al. (2016), while the relationship is slightly weaker. As Germany lacks behind in implementing e-services successfully in comparison to other European countries, the user base could be too small to promote the benefits to friends and family. The limited implemented SEGS even further strengthen this. Surprisingly, FC show no significant influence on BI, while several studies reported a high significance (e.g., Mensah et al. 2020; Rana et al. 2016). This indicates that citizens in Germany already consider themselves very confident in using digital services, and therefore FC have no significant influence on BI. This finding agrees with previous studies on adopting e-government services (e.g., Dwivedi et al. 2015; Verkijika and Wet 2018). FC also strongly impact EE in terms of SEGS. Thus, increasing access by a broad user base through investments in the internet promotes adoption. In other words, the more sophisticated the organizational and technical infrastructure is, the lower the associated degree of EE (Mensah et al. 2020). Significant findings in the past (Mensah et al. 2020; e.g., Verkijika and Wet 2018) indicate a negative influence of PR on ATT. This holds for most technology adoption studies, while perceived risks can differ. Regarding e-government services, citizens fear misuse of their proprietary personal data, e.g., ID or passport number, needed to process such services. This risk is certainly apparent when citizens do not understand the functionalities of advanced technologies to provide smart services.

In addition, our extended model tested for relationships that previously received no attention. This research indicates that RtC significantly and negatively influences BI. The two additional factors, TiI and TiG, significantly negatively impact RtC. Thus, it can be inferred that citizens' lack of trust prevents them from changing their behavior, i.e., adopting SEGS. Nevertheless, TiL and TiG show no significant direct influences on BI. The disparity between the e-government services offered in Germany and its adoption could find a cause in RtC through a lack of trust. Our study confirms the finding by Lallmahomed et al. (2017), who contribute that RtC is a significant negative influence on EE. Thus, we also propose the ease of use of SEGS to foster its adoption and with an even stronger relationship than usual e-government services.

Previous research calls to test technology acceptance models in various contexts tying factors that expand the model and account for geographical differences (Dwivedi et al. 2015; Oliveira et al. 2016). Regarding theoretical implications, our study validates an adapted UMEGA in Germany. Thereby, we followed existing studies and included the constructs of TiI and TiG (Mensah et al. 2020; Verkijika and Wet 2018) and RtC (Lallmahomed et al. 2017). In the context of SEGS in Germany, we can testify that our adapted model greatly exceeds the originally proposed model (Dwivedi et al. 2015) and other studies that applied adapted UMEGA (Avazov and Lee 2022; Mensah et al. 2020; e.g., Verkijika and Wet 2018) regarding the explanatory power of ATT (R^2=0.643), while for BI it shows similar explanatory power (R^2=0.773). Further comparison discloses a least favorable explanatory power for EE (R^2=0.355), while RtC (R^2=0.336) shows a similar result to the study of Lallmahomed et al. (2017). We proved that RtC in our investigated context unfolds a highly significant impact on BI. At the same time, the explanatory power of RtC still leaves room for improvement but is comparable to previous studies (i.e., Lallmahomed et al. 2017).

Our study also has practical implications. Although FC, TiG, and TiI were not supported as a direct facilitating factor for SEGS, other factors can be actively addressed for promoting SEGS in Germany. Above all, PE and EE could be improved through increased user-friendliness and functionality in service applications and streamlining citizen processes (e.g., no on-site attendance). In addition, SI can be leveraged through awareness campaigns, e.g., on social media platforms and by sharing success stories (Dwivedi et al., 2017). Data security and privacy measures should be transparently driven to improve PR. Overall, in practice, e-governance, as in all other digital transformation scenarios, is not only about technical implementation. Many factors, such as the (digital) mindset of the citizens, and willingness to change, are central. Thus, Germany can benefit from initiating a holistic approach, including targeted marketing and communication activities or even training and support for citizens to foster the successful adoption of SEGS Dwivedi et al., 2017).

As with all research, our study has some limitations. Although we can consider RtC important to explain BI on adopting SEGS, the influence of further variables on RtC should be tested in future work to increase its explanatory power. Furthermore, our sample can be characterized as relatively young and digital-savvy, and thus interpretations must recognize this age bias.

In this study, we answered the research question of *which factors influence the citizens' adoption of SEGS*. Thereby, we provide a first attempt to explain what influences the use of SEGS compared to previous studies. We think this to be a promising direction as services tend to become more sophisticated in any context by applying advanced technologies (e.g., AI, IoT). Thus, we hope to contribute to the knowledge base on e-government adoption and spur the research of other scholars to investigate this topic. Precisely, differences in motivational factors of regional and national e-government service providers and between various types of e-government services enhance knowledge. Furthermore, as our study focuses on Germany, future research should shed light on the differences between e-government laggards like Germany and forerunners like Estonia. The mindset of citizens and the differentiation between mandatory and voluntary use are interesting factors that might influence the adoption of SEGS.

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References

Abu-Shanab, E. A. 2017. "E-government familiarity influence on Jordanians' perceptions," *Telematics and Informatics* (34:1), pp. 103-113 (doi: 10.1016/j.tele.2016.05.001).

Ajzen, I. 1980. "Understanding Attitudes and Predicting Social Behavior," *Englewood cliffs*.

Almaiah, M. A., and Nasereddin, Y. 2020. "Factors influencing the adoption of e-government services among Jordanian citizens," *Electronic Government, an International Journal* (16:3), pp. 236-259.

Alshehri, M., Drew, S., and AlGhamdi, R. 2013. "Analysis of Citizens Acceptance for E-government Services: Applying the UTAUT Model," (doi: 10.48550/arXiv.1304.3157).

Avazov, S., and Lee, S. 2022. "E-Government Services Adoption in Uzbekistan: An Empirical Validation of Extended Version of the Unified Model of Electronic Government Acceptance (UMEGA)," *Journal of Policy Studies* (37:3).

Bélanger, F., and Carter, L. 2008. "Trust and risk in e-government adoption," *The Journal of Strategic Information Systems* (17:2), pp. 165-176 (doi: 10.1016/j.jsis.2007.12.002).

Carter, L., and Bélanger, F. 2005. "The utilization of e-government services: citizen trust, innovation and acceptance factors," *Information Systems Journal* (15:1), pp. 5-25.

Carter, L., Schaupp, L. C., Hobbs, J., and Campbell, R. 2012. "E-Government Utilization," *International Journal of Electronic Government Research* (8:1), pp. 83-97 (doi: 10.4018/jegr.2012010105).

Chavan, J. 2013. "Internet banking-benefits and challenges in an emerging economy," *Journal of Research in Business Management,* (1:1), pp. 19-26.

Chin, W. W. 2013. "The partial least squares approach to structural equation modeling," *Modern methods for business research* (295:2), pp. 295-336.

Criado, J. I., and Gil-Garcia, J. R. 2019. "Creating public value through smart technologies and strategies: From digital services to artificial intelligence and beyond," *Int J of Pub Sec Mgt* (32:5), pp. 438-450.

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

Dwivedi, Y. K., Rana, N. P., Janssen, M., Lal, B., Williams, M. D., and Clement, M. 2017. "An empirical validation of a unified model of electronic government adoption (UMEGA)," *Government Information Quarterly* (34:2), pp. 211-230 (doi: 10.1016/j.giq.2017.03.001).

Dwivedi, Y. K., Wastell, D., Laumer, S., Henriksen, H. Z., Myers, M. D., Bunker, D., Elbanna, A., Ravishankar, M. N., and Srivastava, S. C. 2015. "Research on information systems failures and successes: Status update and future directions," *Information Systems Frontiers* (17:1), pp. 143-157.

European Commission. 2020. "Digital Economy and Society Index (DESI) 2020," available at https://ec.europa.eu/commission/presscorner/detail/en/QANDA_20_1022.

Federal Institute of Population Research. 2021. "Average age of the population in Germany (1871-2021) ," available at https://www.bib.bund.de/DE/Fakten/Fakt/B19-Durchschnittsalter-Bevoelkerung-ab-1871.html

Federal Ministry of the Interior, Building and Community. 2019. "Online Access Act," available at https://www.onlinezugangsgesetz.de/Webs/OZG/EN/home/home-node.html;jsessionid=1D877068B8DAC83F84CB974069983591.1_cid350, accessed on Feb 26 2023.

Fornell, C., and Larcker, D. F. 1981. "Evaluating Structural Equation Models with Unobservable Variables and Measurement Error," *Journal of Marketing Research* (18:1), p. 39 (doi: 10.2307/3151312).

Gascó-Hernandez, M. 2018. "Building a smart city: lessons from Barcelona," *Communications of the ACM* (61:4), pp. 50-57.

Hair, J. F., Risher, J. J., Sarstedt, M., and Ringle, C. M. 2019. "When to use and how to report the results of PLS-SEM," *European Business Review* (31:1), pp. 2-24.

Henseler, J., Ringle, C. M., and Sarstedt, M. 2015. "A new criterion for assessing discriminant validity in variance-based structural equation modeling," *J. of the Acad. Mark. Sci.* (43:1), pp. 115-135.

Hirschheim, R., and Newman, M. 1988. "Information Systems and User Resistance: Theory and Practice," *The Computer Journal* (31:5), pp. 398-408 (doi: 10.1093/comjnl/31.5.398).

Hung, S.-Y., Chang, C.-M., and Kuo, S.-R. 2013. "User acceptance of mobile e-government services: An empirical study," *Government Information Quarterly* (30:1), pp. 33-44.

Hung, S.-Y., Tang, K.-Z., Chang, C.-M., and Ke, C.-D. 2009. "User acceptance of intergovernmental services: An example of electronic document management system," *Government Information Quarterly* (26:2), pp. 387-397.

Jethro, O. O., Grace, A. M., and Thomas, A. K. 2012. "E-learning and its effects on teaching and learning in a global age," *Int. Journal of Academic Research in Business and Social Sciences* (2:1), p. 203.

Johnson, P. 2000. *Understanding Management Research*: *An Introduction to Epistemology*, London: Sage Publications Ltd.

Kim, and Kankanhalli. 2009. "Investigating User Resistance to Information Systems Implementation: A Status Quo Bias Perspective," *MIS Quarterly* (33:3), p. 567 (doi: 10.2307/20650309).

Kumar, R., and Ali, M. M. 2020. "A review on chatbot design and implementation techniques," *International Journal of Engineering Technology* (7:11).

Kurfalı, M., Arifoğlu, A., Tokdemir, G., and Paçin, Y. 2017. "Adoption of e-government services in Turkey," *Computers in Human Behavior* (66), pp. 168-178 (doi: 10.1016/j.chb.2016.09.041).

Lallmahomed, M. Z., Lallmahomed, N., and Lallmahomed, G. M. 2017. "Factors influencing the adoption of e-Government services in Mauritius," *Telematics and Informatics* (34:4), pp. 57-72.

Lu, C.-T., Huang, S.-Y., and Lo, P.-Y. 2010. "An empirical study of on-line tax filing acceptance model: Integrating TAM and TPB," *African journal of business management* (4:5), p. 800.

Mensah, I. K., Zeng, G., and Luo, C. 2020. “E-Government Services Adoption: An Extension of the Unified Model of Electronic Government Adoption,” *SAGE Open* (10:2), 215824402093359.

Moore, G. C., and Benbasat, I. 1991. “Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation,” *Information Systems Research* (2:3), pp. 192-222.

Nayak, K. M., Bhatt, V., and Nagvadia, J. 2021. “Measuring impact of factors influencing to consumer buying intention with respect to online shopping,” *Int. Journal of Management* (12:1), pp. 230-242.

Nov, O., and Ye, C. 2009. “Resistance to change and the adoption of digital libraries: An integrative model,” *Journal of the American Society for Information Science and Technology* (60:8), pp. 1702-1708 (doi: 10.1002/asi.21068).

Oliveira, T., Thomas, M., Baptista, G., and Campos, F. 2016. “Mobile payment: Understanding the determinants of customer adoption and intention to recommend the technology,” *Computers in Human Behavior* (61), pp. 404-414 (doi: 10.1016/j.chb.2016.03.030).

Rana, N. P., Dwivedi, Y. K., Lal, B., Williams, M. D., and Clement, M. 2017. “Citizens’ adoption of an electronic government system: towards a unified view,” *Inf Syst Front* (19:3), pp. 549-568.

Rana, N. P., Dwivedi, Y. K., Williams, M. D., and Weerakkody, V. 2015. “Investigating success of an e-government initiative: Validation of an integrated IS success model,” *Inf Syst Front* (17:1), pp. 127-142.

Rana, N. P., Dwivedi, Y. K., Williams, M. D., and Weerakkody, V. 2016. “Adoption of online public grievance redressal system in India: Toward developing a unified view,” *Computers in Human Behavior* (59), pp. 265-282 (doi: 10.1016/j.chb.2016.02.019).

Shalini, R. T. 2009. “Are Mauritians ready for e-Government services?” *Government Information Quarterly* (26:3), pp. 536-539 (doi: 10.1016/j.giq.2008.12.016).

Straub, D. W., and Welke, R. J. 1998. “Coping with Systems Risk: Security Planning Models for Management Decision Making,” *MIS Quarterly* (22:4), p. 441 (doi: 10.2307/249551).

Taylor, S., and Todd, P. 1995. “Decomposition and crossover effects in the theory of planned behavior: A study of consumer adoption intentions,” *Int Journal of Research in Marketing* (12:2), pp. 137-155.

Thao, V. T. T. 2017. “The effect of power distance on e-government adoption in Vietnam: Empirical investigation using UTAUT model,” *International Journal of Innovative Science, Engineering and Technology* (4:5), pp. 245-249.

Urbach, N., and Ahlemann, F. 2010. “Structural equation modeling in information systems research using partial least squares,” *Journal of Information Technology Theory and Application* (11:2), p. 2.

Velsberg, O., Westergren, U. H., and Jonsson, K. 2020. “Exploring smartness in public sector innovation - creating smart public services with the Internet of Things,” *European Journal of Information Systems* (29:4), pp. 350-368 (doi: 10.1080/0960085X.2020.1761272).

Venkatesh, Morris, and Davis. 2003. “User Acceptance of Information Technology: Toward a Unified View,” *MIS Quarterly* (27:3), p. 425.

Venkatesh, Thong, and Xu. 2012. “Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology,” *MIS Quarterly* (36:1), p. 157.

Verkijika, S. F., and Wet, L. de. 2018. “E-government adoption in sub-Saharan Africa,” *Electronic Commerce Research and Applications* (30), pp. 83-93 (doi: 10.1016/j.elerap.2018.05.012).

Warkentin, M., Gefen, D., Pavlou, P. A., and Rose, G. M. 2002. “Encouraging Citizen Adoption of e-Government by Building Trust,” *Electronic Markets* (12:3), pp. 157-162.

Weerakkody, V., El-Haddadeh, R., Al-Sobhi, F., Shareef, M. A., and Dwivedi, Y. K. 2013. “Examining the influence of intermediaries in facilitating e-government adoption: An empirical investigation,” *International Journal of Information Management* (33:5), pp. 716-725.

Zhao, F., and Khan, M. S. 2013. “An Empirical Study of E-Government Service Adoption: Culture and Behavioral Intention,” *International Journal of Public Administration* (36:10), pp. 710-722.

Zuiderwijk, A., Janssen, M., and Dwivedi, Y. K. 2015. “Acceptance and use predictors of open data technologies: Drawing upon the unified theory of acceptance and use of technology,” *Government Information Quarterly* (32:4), pp. 429-440 (doi: 10.1016/j.giq.2015.09.005).