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CITIZEN PARTICIPATION IN ELECTRONIC PUBLIC ADMINISTRATION: THE CONSIDERATIONS OF FUNCTIONALITY AND THE TECHNOLOGY ACCEPTANCE MODEL

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ABSTRACT

The adoption of technology-based public administration has revealed the ability of virtual spaces to accelerate public services, making them more effective and accessible. However, technology-based public services also have negative effects relating to the lack of citizen supervision and the possible misuse of personal data. This study analyzed the effects of functionality and data privacy on the perceived usefulness and perceived ease of use of technology in Indonesian public administration, using administrators as respondents. An empirical analysis was conducted using quantitative methods with the help of the WarpPLS (Partial Least Squares) program. The results showed that data privacy and functionality have positive effects on perceived ease of use (PEU) and perceived benefits (PB). Furthermore, the statistical results showed that PEU and PB had positive effects on citizen participation in electronic public administration. The results of testing the mediating effects of PB revealed its role in strengthening the positive and significant effects of the functionality and data privacy variables on citizen participation in use. On a theoretical level, these results contribute to an explanation of the application of the technology acceptance model in the online public sector and underline the crucial elements that influence technology acceptance.

Contribution/Originality: Theoretically, this study contributes to the explanation of the application of the technology acceptance model in the online public sector and underscores the important elements that influence technology acceptance among citizens. Practically, this study encourages public sector administrators who provide public services in a technology-laden era to ensure that citizens are more aware of and involved in electronic public services.

1. INTRODUCTION

Technology use in the public sector has developed rapidly in recent years. The Covid-19 pandemic has driven a massive and intensive increase in technology use in public administration, moving public services from the physical to the virtual space. Several studies have confirmed the important role of technology while revealing its effects, both positive and negative, on government achievement and delivery of public services (Heflin, Shewmaker, & Nguyen, 2017; Rashid & Asghar, 2016; Xu, Wang, Peng, & Wu, 2019). Technology-based public administration has revealed virtual spaces' ability to accelerate public service delivery, making public services more effective and accessible (Al-

Debei, Akroush, & Ashouri, 2016; Debreceny, Gray, Ng, Lee, & Yau, 2005; Ganasegeran, Renganathan, Rashid, & Al-Dubai, 2017; Mulyana et al., 2022; Wilson, Hargreaves, & Hauxwell-Baldwin, 2017; Yu, Lee, Ha, & Zo, 2017). However, technology-based public services also have negative effects relating to a lack of citizen supervision and the possible misuse of personal data (Dimitropoulos, Patel, Scheffler, & Posnack, 2011; Dos Santos, Cappellozza, & Albertin, 2018; Ziefle, Halbey, & Kowalewski, 2016).

The increased use of virtual space in public services has inspired various platforms to create products to serve this need, such as in population administration (Totanan, 2022). The rapid development of digital technology has made public services faster and more effective. Public sector technology has been structured as a systematic framework that aims to design, implement, and evaluate the entire public services process by utilizing the role of technology (Al-Emran & Salloum, 2017; Al-Maroof, Alfaisal, & Salloum, 2021). In addition, the use of technology helps manage and solve problems relating to public service performance (Berque & Newman, 2015; Dehghani, 2016). Strict social restrictions during the Covid-19 pandemic forced public sector stakeholders to use digital technology to keep services running. This initially required citizens and administrators to integrate themselves with and adopt these technologies (Bakar, 2018; Hallström & Schönborn, 2019; Kunter et al., 2013; Lauermann & König, 2016).

Several studies have confirmed that technology adoption is determined by several factors, such as perceptions of convenience and possible benefits. In general, this view has led to the development of the Technology Acceptance Model (TAM) theory, which highlights the crucial elements that influence technology acceptance in public administration (Davis, Bagozzi, & Warshaw, 1989; Davis, 1989; Lai, 2017; Nugroho, Bakar, & Ali, 2017; Pudjiarti, Lisdiyono, & Werdiningsih, 2022). In this study, the model used is that of AlHamad et al. (2021). The empirical relationship tested regards the role of the independent variables of functionality and data privacy on the perceived ease of use and usefulness. This framework ultimately reveals the extent to which these factors predict citizens' interest in engaging with electronic public administration.

2. LITERATURE REVIEW AND HYPOTHESES

2.1. Functionality, Perceived Benefits, and Perceived Ease of Use

Functionality refers to the degree to which the service offered by the provider has practical value in accordance with the goals desired by the user (Tandon, Kiran, & Sah, 2018). Functionality is closely related to software technology and computer hardware. This element of functionality leads to a design that fulfills a supportive function in safely and conveniently managing and integrating data. Ford, Pritoni, Sanguinetti, and Karlin (2017) identified potential benefits and information related to usage and convenience as the main drivers of technology adoption in terms of functionality. Sovacool and Del Rio (2020) identified control systems, practical elements, and socio-technical functions as important elements driving technology adoption. Previous studies have emphasized the very close relationship between functionality and perceived benefits (Al-Debei et al., 2016; Wilson et al., 2017) and perceptions of ease of use (Rao et al., 2011; Tandon et al., 2018). Based on these considerations, the following hypotheses are proposed in this study:

H1. Functionality has a positive and significant effect on perceived benefits.
H2. Functionality has a positive and significant effect on perceived ease of use.

2.2. Data Privacy, Perceived Benefits, and Perceived Ease of Use

Data security and confidentiality play a crucial role for users and service providers (Dhagarra, Goswami, & Kumar, 2020; Shank, Wright, Lulham, & Thurgood, 2021). Platforms, applications, and products that are perceived as safe by users are more likely to be used intensively than products that are considered less secure. According to Bertino (1998), every organization needs to assure its users of the usability and quality of data by implementing access control, authorization, fault tolerance, and recovery processes. In general, data privacy refers to limiting the

disclosure of personal information to unauthorized parties. This, in turn, ensures that data is used appropriately between users and service providers and limits the uncontrolled sharing of data. Since data security and privacy are closely related to the use of the internet and digital technologies, data privacy positively affects perceived benefits (Dimitropoulos et al., 2011; Ziefle et al., 2016) and perceived ease of use (Distler, Lallemand, & Koenig, 2020; Schnall, Higgins, Brown, Carballo-Dieguez, & Bakken, 2015).

H3. Data privacy has a positive and significant effect on perceived benefits.

H4. Data privacy has a positive and significant effect on perceived ease of use.

2.3. Perceived Ease of Use, Perceived Benefits, and Citizen Participation Behavior

According to Chen and Aklikokou (2020), perceived usefulness and perceived ease of use affect technology adoption, and this is reflected by the citizen participation behavior that ensues. According to Davis et al. (1989), perceived usefulness refers to the user's expectations of the technology's ability to increase potential performance. Furthermore, according to Mois and Beer (2020), perceived ease of use refers to the perceived amount of effort required to use the technology effectively (Davis, 1989). Several previous studies have confirmed the effect of perceived ease of use on perceived benefits, where the greater the user's perception of the convenience of the product, the greater their perception of the potential benefits they can obtain (Abdullah, Ward, & Ahmed, 2016; Moslehpour, Pham, Wong, & Bilgiçli, 2018). This is because users will be more inclined to use technology that is easy to use, compared with technology that does not offer the same convenience. Based on these considerations, the following hypothesis is proposed in this study:

H5. There is a positive and significant effect of perceived ease of use on perceived benefits.

Hsu, Chen, and Ting (2018) found that the two main components of TAM, perceived ease of use and perceived benefits, have a positive effect on technology adoption. Likewise, Al-Rahmi et al. (2021) found that factors such as compatibility, enjoyment, and relative advantage have a substantial impact on perceived usefulness, which ultimately affects citizen participation in public sector technology use. Al-Adwan (2020) found that perceived ease of use and perceived usefulness significantly influence citizens' participation behavior in online public sector courses. Several other studies have found an effect of perceived ease of use and perceived benefits on citizen participation in the use of public sector technology (Berque & Newman, 2015; Dehghani, 2016).

H6. Perceived ease of use has a positive and significant effect on citizen participation in the use of electronic public administration.

H7. Perceived benefits have a positive and significant effect on citizen participation in the use of electronic public administration.

3. METHOD

This study analyzes the effects of functionality and data privacy on perceived benefits and perceived ease of use of electronic technology in Indonesian public administration. In addition, an empirical analysis was carried out to analyze the effect of perceived ease of use on the perceived benefits of and citizen participation in electronic public administration, as well as the effect of perceived benefits on citizen participation in the use of electronic public administration, see Figure 1. To analyze these various effects, empirical tests were conducted using a quantitative approach. The model used replicates that of AlHamad et al. (2021).

In this study, functionality is defined operationally as the degree to which the service offered by the provider has a practical value in accordance with the intended purpose of the user, using a 3-item measure adopted from Sovacool and Del Rio (2020). The data privacy variable is defined as limiting the disclosure of personal information to unauthorized parties and ensuring that data is used appropriately between users and service providers, as well as limiting uncontrolled data sharing; the variable's measure was adopted from Dhagarra et al. (2020).
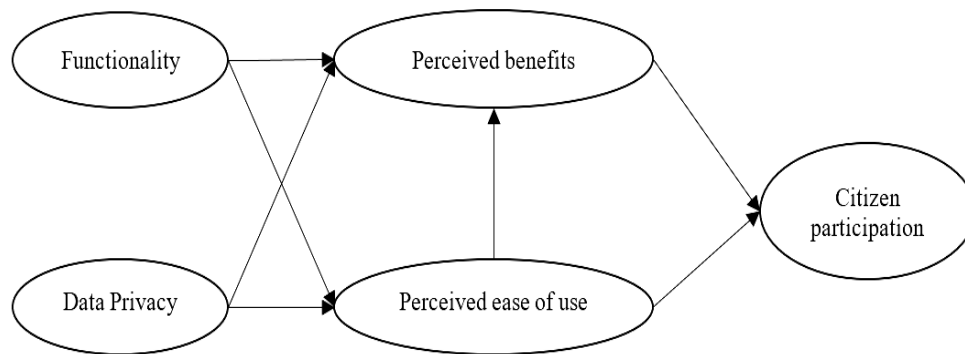
Figure 1. Theoretical framework.

Furthermore, the perceived benefits variable is defined as the user's expectation of the technology's ability to increase potential performance, which refers to the theoretical conceptualization of Davis (1989). Perceived ease of use in this study refers to the amount of effort required to use the technology effectively (Davis, 1989). Finally, the citizen participation variable is defined as the willingness of users to use digital technology to meet their specific needs, with the measure used adopted from Kasilingam (2020).

To enable the empirical analysis to be carried out, this study used administrators as respondents. Sampling was performed using a purposive random sampling technique. Questionnaires were distributed to respondents in Bandung Regency, West Java, Indonesia. A total of 282 questionnaires were distributed, and 158 questionnaires were returned, entailing a response rate of 56 percent. The scale used in the questionnaire was a 5-point Likert scale. Data analysis was conducted using WarpPLS.

4. RESULTS

The results of the outer loadings are shown in Table 1. Outer loadings inform the loading factor, which shows the magnitude of the correlation between indicators and latent variables. A loading factor value greater than 0.7 for each indicator is said to be valid. The test results show that all variables of functionality (FN), data privacy (DP), perceived ease of use (PEU), perceived benefits (PB), and citizen participation in use (IU) had an indicator with a loading factor value greater than 0.7. Thus, the indicators used in this study were all valid.

Table 1. Outer loading.

Items	Functionality (FN)	Data Privacy (DP)	Perceived Ease of Use (PEU)	Perceived Benefits (PB)	Citizen Participation in Use (IU)
FN1	0.852				
FN2	0.878				
FN3	0.857				
DP1		0.813			
DP2		0.874			
DP3		0.896			
PEU1			0.878		
PEU2			0.828		
PEU3			0.883		
PB1				0.882	
PB2				0.859	
PB3				0.829	
IU1					0.755
IU2					0.940
IU3					0.963

Note: FN= Functionality; DP= Data Privacy; PEU= Perceived Ease of Use; PB= Perceived Benefits; IU= Citizen Participation in Use.

The results of the discriminant validity analysis are shown in Table 2. Discriminant validity relates to the principle that different constructs of measures should not be highly correlated. Discriminant validity occurs when two different instruments measure two constructs that are predicted to be uncorrelated, resulting in a score that is not correlated. The test results show various values for the relationships between the variables in this study. Specifically, medium values were shown between IU and FN (0.618), IU and DP (0.600), IU and PEU (0.482), and IU and PB (0.764). Aside from these, the values generated from the discriminant validity test were in the low category, below 0.4.

Table 2. Discriminant validity.

Variable	Functionality (FN)	Data Privacy (DP)	Perceived Ease of Use (PEU)	Perceived Benefits (PB)	Citizen Participation in Use (IU)
FN	0.863				
DP	0.330	0.862			
PEU	0.392	0.401	0.863		
PB	0.391	0.365	0.399	0.857	
IU	0.618	0.600	0.482	0.764	0.891

Note: FN= Functionality; DP= Data Privacy; PEU= Perceived Ease of Use; PB= Perceived Benefits; IU= Citizen Participation in Use.

The results of the reliability test, shown in Table 3, reveal Cronbach's alpha values higher than 0.6. Specifically, the Cronbach's alpha values were 0.828 (FN), 0.829 (DP), 0.830 (PEU), 0.819 (PB), and 0.871 (IU). The results also show that the rho_A and composite reliability values were greater than 0.8 for all variables. The Average Variance Extracted (AVE) values of all variables were greater than 0.7. Thus, the variables were declared reliable.

Table 3. Reliability.

Variable	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Functionality (FN)	0.828	0.833	0.897	0.744
Data Privacy (DP)	0.829	0.860	0.896	0.742
Perceived Ease of Use (PEU)	0.830	0.841	0.898	0.745
Perceived Benefits (PB)	0.819	0.826	0.892	0.734
Citizen Participation in Use (IU)	0.871	0.943	0.919	0.794

Furthermore, the R-squared test was carried out to analyze the proportion of variation in the dependent variable that could be predicted from each independent variable. The test results in Table 4 show the R-squared adjusted value for the dependent variables in this study, namely PEU, PB, and IU, which had values of 0.227, 0.240, and 0.616, respectively. This shows that the independent variables of functionality and data privacy can predict 22.7 percent and 24 percent of variations in perceived ease of use (PEU) and perceived benefits (PB), respectively. Furthermore, the dependent variable of citizen participation in use (IU) was predicted with a higher variation value, namely 0.621, than the independent variables in this study.

Table 5 presents the prediction relevance or Q-squared results. This test was carried out to analyze the prediction capability with the blindfolding procedure. The criteria used were 0.02 for small, 0.15 for medium, and 0.35 for large. The results in Table 5 show that the value of Q^2 (=1-SSE/SSO) for PEU was 0.167 (medium), PB = 0.174 (medium), and IU = 0.460 (large).

Table 4. R-squared results.

Variables	R Squared	R Squared Adjusted
PEU	0.237	0.227
PB	0.255	0.240
IU	0.621	0.616

Note: PEU= Perceived Ease of Use; PB= Perceived Benefits; IU= Citizen Participation in Use.

Table 5. Q-squared results.

Variables	SSO	SSE	Q² (= 1-SSE/SSO)
FN	474.000	474.000	
DP	474.000	474.000	
PEU	474.000	394.724	0.167
PB	474.000	391.521	0.174
IU	474.000	255.807	0.460

Note: SSO = Single Sign On; SSE = Sum Squared Error; FN= Functionality; DP= Data Privacy; PEU= Perceived Ease of Use; PB= Perceived Benefits; IU= Citizen Participation in Use.

The results of the model fit test, shown in Table 6, reveal that the model's fit was acceptable, both the saturated model and the estimated model. This indicates that the model used in this study satisfied all the set indices and confirms that the formulated model could be applied in further tests.

Table 6. Model fit.

Indices	Saturated Model	Estimated Model
SRMR	0.085	0.121
d_ULS	0.870	1.752
d_G	0.540	0.669
Chi-Square	426.304	474.384
NFI	0.735	0.705

Note: SRMR = Standardized Root Mean Square Residual; d_ULS = Unweighted Least Squares Discrepancy; d_G = Geodesic Discrepancy; NFI = Normed Fit Index.

Furthermore, hypothesis testing was carried out, and the results are detailed in Table 7. The statistical results showed a positive and significant effect of functionality (FN) on perceived benefits (PB), as indicated by the Original Sample (O) value obtained of 0.237, Sample Mean (M) of 0.237, Standard Deviation (STDEV) of 0.080, T Statistics (|O/STDEV|) of 2.967, and *p-*value of 0.003. Thus, the first hypothesis is accepted. These results are in agreement with Al-Debei et al. (2016), Debreceny et al. (2005), Ganasegeran et al. (2017), Wilson et al. (2017), and Yu et al. (2017), who found that functionality was a determinant of benefits perceived by users.

Table 7. Path coefficient and significance test results.

Hypotheses	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
FN -> PB	0.237	0.237	0.080	2.967	0.003
FN -> PEU	0.292	0.298	0.075	3.892	0.000
DP -> PB	0.195	0.197	0.083	2.344	0.019
DP -> PEU	0.305	0.303	0.079	3.878	0.000
PEU -> PB	0.228	0.224	0.081	2.805	0.005
PEU -> IU	0.210	0.209	0.061	3.472	0.001
PB -> IU	0.680	0.685	0.044	15.444	0.000

Note: FN= Functionality; DP= Data Privacy; PEU= Perceived Ease of Use; PB= Perceived Benefits; IU= Citizen Participation in Use.

Testing the second hypothesis, the effect of FN -> PEU, obtained an Original Sample (O) value of 0.292, Sample Mean (M) of 0.298, Standard Deviation (STDEV) of 0.075, T Statistics (|O/STDEV|) of 3.892, and p-value of 0.000, indicating a positive and significant effect of functionality (FN) on perceived ease of use (PEU ($p < 0.05$).

Thus, the second hypothesis, stating a positive and significant effect of functionality (FN) on perceived ease of use (PEU) is empirically proven and accepted. This result is consistent with previous research that underscored the important role of data security and privacy in users' ease-of-use perceptions (Abdullah et al., 2016; Brown, 2002; Rao et al., 2011; Ryan & Rao, 2008; Tandon et al., 2018).

The results of testing the third hypothesis showed a positive and significant effect of data privacy (DP) on perceived benefits (PB), indicated by the Original Sample (O) value of 0.195, Sample Mean (M) of 0.195, Standard Deviation (STDEV) of 0.083, T Statistics (|O/STDEV|) of 2.344, and p-value of 0.019 (< 0.05). Thus, the third hypothesis is accepted. This result is in agreement with Ziefle et al. (2016), Dimitropoulos et al. (2011), Dos Santos et al. (2018), and Brell, Philipsen, and Ziefle (2019), who stated that data security and privacy are closely related to the use of the internet and digital technology, which has a positive effect on perceived benefits.

Furthermore, testing the fourth hypothesis, the effect of data privacy (DP) on perceived ease of use (PEU), provided an Original Sample (O) value of 0.305, Sample Mean (M) of 0.303, Standard Deviation (STDEV) of 0.079, T Statistics (|O/STDEV|) of 3.878, and p-value of 0.000. Thus, the fourth hypothesis, which stated a positive and significant effect of data privacy (DP) on perceived ease of use (PEU), is empirically proven and accepted. This is consistent with previous research that highlighted the critical role of data privacy in users' perceptions of convenience (Distler et al., 2020; Schnall et al., 2015). The more users trust in the security of their personal data, the more intensively they will use a technology product.

Next, testing the fifth hypothesis, which stated the positive effect of perceived ease of use (PEU) on perceived benefits (PB), provided an Original Sample (O) value of 0.228, Sample Mean (M) of 0.224, Standard Deviation (STDEV) of 0.081, T Statistics (|O/STDEV|) of 2.805, and p-value of 0.005. This means that there was a positive and significant effect of perceived ease of use (PEU) on perceived benefit (PB), as indicated by the p-value < 0.05. Thus, the fifth hypothesis is accepted. This aligns with Moslehpour et al. (2018), Ozturk, Bilgihan, Nusair, and Okumus (2016), and Abdullah et al. (2016), who indicated that users are more inclined to use technology that is easy to use, compared with technology that does not offer the same convenience.

The sixth hypothesis postulated a positive and significant effect of perceived ease of use (PEU) on citizen participation in use (IU). The results show an Original Sample (O) value of 0.210, Sample Mean (M) of 0.209, Standard Deviation (STDEV) of 0.061, T Statistics (|O/STDEV|) of 3.472, and p-value of 0.001. Thus, perceived ease of use (PEU) had a positive and significant effect on citizen participation in use (IU), and the sixth hypothesis is accepted. This is in accordance with Hsu et al. (2018), who found that perceived ease of use and perceived benefits had a positive effect on technology adoption, and with Al-Rahmi et al. (2021), who found that items such as compatibility, enjoyment, and relative advantage had a substantial impact on perceived usefulness, which ultimately influenced citizen participation in public sector technology use.

Table 8. Indirect effect.

Indirect relationship	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
DP -> PEU -> PB -> IU	0.047	0.045	0.019	2.428	0.016
FN -> PEU -> PB	0.066	0.067	0.032	2.097	0.036
FN -> PEU -> IU	0.061	0.063	0.027	2.295	0.022
DP -> PEU -> IU	0.064	0.065	0.028	2.256	0.025
DP -> PEU -> PB	0.069	0.066	0.029	2.433	0.015
FN -> PB -> IU	0.161	0.163	0.057	2.814	0.005
FN -> PEU -> PB -> IU	0.045	0.046	0.022	2.074	0.039
PEU -> PB -> IU	0.155	0.153	0.057	2.714	0.007
DP -> PB -> IU	0.133	0.136	0.060	2.200	0.028

Note: FN= Functionality; DP= Data Privacy; PEU= Perceived Ease of Use; PB= Perceived Benefits; IU= Citizen Participation in Use.

Table 9. Total effect.

Relationship	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
FN -> PEU	0.292	0.298	0.075	3.892	0.000
FN -> PB	0.303	0.304	0.070	4.306	0.000
FN -> IU	0.268	0.272	0.057	4.706	0.000
DP -> PEU	0.305	0.303	0.079	3.878	0.000
DP -> PB	0.265	0.264	0.084	3.163	0.002
DP -> IU	0.244	0.246	0.061	4.028	0.000
PEU -> PB	0.228	0.224	0.081	2.805	0.005
PEU -> IU	0.365	0.362	0.062	5.871	0.000
PB -> IU	0.680	0.685	0.044	15.444	0.000

Note: FN= Functionality; DP= Data Privacy; PEU= Perceived Ease of Use; PB= Perceived Benefits; IU= Citizen Participation in Use.

Finally, the results of testing the seventh hypothesis revealed an Original Sample (O) value of 0.680, Sample Mean (M) of 0.685, Standard Deviation (STDEV) of 0.044, T Statistics (\|O/STDEV\|) of 15,444, and *p*-value of 0.000. This shows that the hypothesis, which stated a positive and significant effect of perceived benefit (PB) on citizen participation in use (IU) is empirically proven, and the seventh hypothesis is accepted. These results are consistent with Al-Adwan (2020), Al-Maroof et al. (2021), Al-Emran and Salloum (2017), Berque and Newman (2015), and Dehghani (2016), who found that perceived ease of use and perceived usefulness significantly influenced citizens' participation in online public sector courses.

The indirect effects were then tested to analyze the mediating role of the perceived ease of use (PEU) and perceived benefits (PB) variables in bridging the relationship between the functionality and data privacy variables and citizen participation in use. The test results for the indirect effect are shown in Table 8 and those for the total effect in Table 9. Overall, the results show that perceived ease of use (PEU) and perceived benefits (PB) mediate the relationship between the functionality and data privacy variables and citizen participation in use. Figure 2 illustrates that perceived ease of use (PEU), and perceived benefits (PB) are likely to strengthen the positive and significant effects of functionality (FN) and data privacy (DP) on citizen participation in electronic public administration.
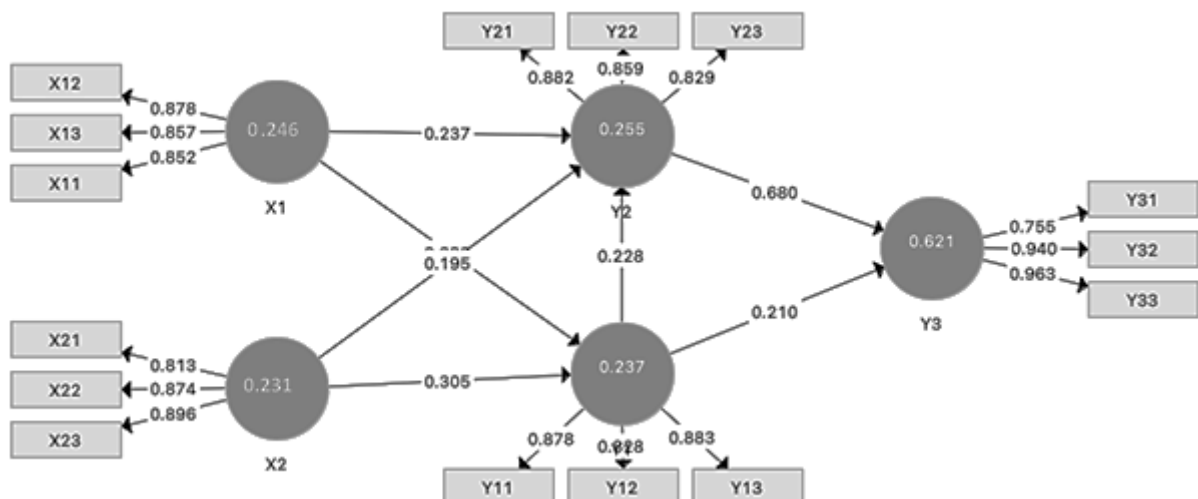

Figure 2. Estimation results.

In general, today's increasingly intensive adoption of technology in the public sector requires administrators to improve citizen involvement in digital public services. Moreover, administrators need a high level of digital knowledge and skills to deliver public services professionally (Lauermann & König, 2016). Public service

administrators can implement and apply digital and online technologies to improve appropriate public services, but they must develop reliable and safe electronic services in the public sector to increase citizen engagement with digital technology in public services (Bakar, 2018). Citizens must thus be encouraged to increase their willingness to participate in technology when obtaining public services (Kunter et al., 2013; Wijiastuti & Nurhayati, 2021). To monitor the progress of public services, citizens can appropriately supervise the public sector by using the available channels (Hallström & Schönborn, 2019). Another indicator that shows that a person is engaged is being able to equip others with knowledge of appropriate public administration techniques by combining time, energy, materials, and abilities (Blau, 1964).

5. CONCLUSION

The results of the study have shown that data privacy and functionality have a positive effect on the perceived ease of use (PEU) and perceived benefits (PB) of technology. Furthermore, the statistical results have shown that PEU and PB have a positive effect on citizen participation in electronic public administration. The results of testing the mediating effects of PB revealed its role in strengthening the positive and significant effects of the functionality and data privacy variables on citizen participation in electronic public administration.

On a theoretical level, these results contribute to an explanation of the application of the technology acceptance model in the online public sector and underline the crucial elements that influence technology acceptance among citizens. Practically, the results are useful for encouraging public sector administrators, when delivering public services in a technology-laden era, to ensure citizens are more aware and involved in electronic public services. A limitation of this study is that more respondents would be required to generalize the findings. In addition, the variables used in this study need to be further developed in future research. Therefore, it is recommended that future research use more respondents and investigate variables that were not tested in this study to analyze the factors affecting technology acceptance in the public sector.

REFERENCES

Abdullah, F., Ward, R., & Ahmed, E. (2016). Investigating the influence of the most commonly used external variables of TAM on students' perceived ease of use and perceived usefulness of e-portfolios. *Computers in Human Behavior, 63*(C), 75-90.Available at: https://doi.org/10.1016/j.chb.2016.05.014.

Al-Adwan, A. S. (2020). Investigating the drivers and barriers to MOOCs adoption: The perspective of TAM. *Education and Information Technologies, 25*(6), 5771-5795.Available at: https://doi.org/10.1007/s10639-020-10250-z.

Al-Debei, M. M., Akroush, M. N., & Ashouri, M. I. (2016). Consumer attitudes towards online shopping. *Internet Research: Electronic Networking Applications and Policy, 26*(1), 707-733.

Al-Emran, M., & Salloum, S. A. (2017). Students' attitudes towards the use of mobile technologies in e-evaluation. *International Journal on Interactive Design Mobile Technology, 11*(5), 195-202.Available at: https://doi.org/10.3991/ijim.v11i5.6879.

Al-Maroof, R. S., Alfaisal, A. M., & Salloum, S. A. (2021). Google glass adoption in the educational environment: A case study in the Gulf area. *Education and Information Technologies, 26*(3), 2477-2500.Available at: https://doi.org/10.1007/s10639-020-10367-1.

Al-Rahmi, W. M., Yahaya, N., Alamri, M. M., Alyoussef, I. Y., Al-Rahmi, A. M., & Kamin, Y. B. (2021). Integrating innovation diffusion theory with technology acceptance model: Supporting students' attitude towards using a massive open online courses (MOOCs) systems. *Interactive Learning Environments, 29*(8), 1380-1392.Available at: https://doi.org/10.1080/10494820.2019.1629599.

98

AlHamad, M., Akour, I., Alshurideh, M., Al-Hamad, A., Kurdi, B., & Alzoubi, H. (2021). Predicting the intention to use google glass: A comparative approach using machine learning models and PLS-SEM. *International Journal of Data and Network Science, 5*(3), 311-320.Available at: https://doi.org/10.5267/j.ijdns.2021.6.002.

Bakar, R. (2018). The influence of professional teachers on Padang vocational school students' achievement. *Kasetsart Journal of Social Sciences, 39*(1), 67-72.Available at: https://doi.org/10.1016/j.kjss.2017.12.017.

Berque, D. A., & Newman, J. T. (2015). *Glass class: Exploring the design implementation and acceptance of google glass in the classroom.* Paper presented at the International Conference on Virtual Augmented and Mixed Reality, Springer.

Bertino, E. (1998). Data security. *Data & Knowledge Engineering, 25*(1-2), 199-216.

Blau, P. M. (1964). *Exchange and power in social life.* New York: John Wiley and Sons.

Brell, T., Philipsen, R., & Ziefle, M. (2019). sCARy! risk perceptions in autonomous driving: The influence of experience on perceived benefits and barriers. *Risk Analysis, 39*(2), 342-357.Available at: https://doi.org/10.1111/risa.13190.

Brown, I. T. (2002). Individual and technological factors affecting perceived ease of use of web-based learning technologies in a developing country. *The Electronic Journal of Information Systems in Developing Countries, 9*(1), 1-15.Available at: https://doi.org/10.1002/j.1681-4835.2002.tb00055.x.

Chen, L., & Aklikokou, A. K. (2020). Determinants of e-government adoption: Testing the mediating effects of perceived usefulness and perceived ease of use. *International Journal of Public Administration, 43*(10), 850-865.Available at: https://doi.org/10.1080/01900692.2019.1660989.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35*(8), 982-1003.Available at: https://doi.org/10.1287/mnsc.35.8.982.

Davis, F. (1989). Perceived usefulness perceived ease of use and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340.Available at: https://doi.org/10.2307/249008.

Debreceny, R. S., Gray, G. L., Ng, J. J.-J., Lee, K. S.-P., & Yau, W.-F. (2005). Embedded audit modules in enterprise resource planning systems: Implementation and functionality. *Journal of Information Systems, 19*(2), 7-27.Available at: https://doi.org/10.2308/jis.2005.19.2.7.

Dehghani, M. (2016). *An assessment towards adoption and diffusion of smart wearable technologies by consumers: The cases of smart watch and fitness wristband products.* Paper presented at the In HT Extended Proceedings.

Dhagarra, D., Goswami, M., & Kumar, G. (2020). Impact of trust and privacy concerns on technology acceptance in healthcare: An Indian perspective. *International Journal of Medical Informatics, 141*, 104164.Available at: https://doi.org/10.1016/j.ijmedinf.2020.104164.

Dimitropoulos, L., Patel, V., Scheffler, S. A., & Posnack, S. (2011). Public attitudes toward health information exchange: Perceived benefits and concerns. *The American Journal of Managed Care, 17*(12 Spec No), SP111-116.

Distler, V., Lallemand, C., & Koenig, V. (2020). How acceptable is this? How user experience factors can broaden our understanding of the acceptance of privacy trade-offs. *Computers in Human Behavior, 106*, 1-10.Available at: https://doi.org/10.1016/j.chb.2019.106227.

Dos Santos, J. G., Cappellozza, A., & Albertin, A. L. (2018). Antecedents of perceived benefits of compliance towards organizational data protection policies. *IEEE Latin America Transactions, 16*(3), 891-896.Available at: https://doi.org/10.1109/tla.2018.8358670.

Ford, R., Pritoni, M., Sanguinetti, A., & Karlin, B. (2017). Categories and functionality of smart home technology for energy management. *Building and Environment, 123*, 543-554.Available at: https://doi.org/10.1016/j.buildenv.2017.07.020.

Ganasegeran, K., Renganathan, P., Rashid, A., & Al-Dubai, S. A. R. (2017). The m-Health revolution: Exploring perceived benefits of WhatsApp use in clinical practice. *International Journal of Medical Informatics, 100*(97), 145-151.Available at: https://doi.org/10.1016/j.ijmedinf.2016.10.013.

Hallström, J., & Schönborn, K. J. (2019). Models and modelling for authentic STEM education: Reinforcing the argument. *International Journal of STEM Education, 6*(1), 1-10.Available at: https://doi.org/10.1186/s40594-019-0178-z.

Heflin, H., Shewmaker, J., & Nguyen, J. (2017). Impact of mobile technology on student attitudes engagement and learning. *Computers & Education, 100*(107), 91-99.Available at: https://doi.org/10.1016/j.compedu.2017.01.006.

Hsu, J.-Y., Chen, C.-C., & Ting, P.-F. (2018). Understanding MOOC continuance: An empirical examination of social support theory. *Interactive Learning Environments, 26*(8), 1100-1118.Available at: https://doi.org/10.1080/10494820.2018.1446990.

Kasilingam, D. L. (2020). Understanding the attitude and intention to use smartphone chatbots for shopping. *Technology in Society, 62*, 101280.Available at: https://doi.org/10.1016/j.techsoc.2020.101280.

Kunter, M., Klusmann, U., Baumert, J., Richter, D., Voss, T., & Hachfeld, A. (2013). Professional competence of teachers: Effects on instructional quality and student development. *Journal of Educational Psychology, 105*(3), 805-8020.Available at: https://doi.org/10.1037/a0032583.

Lai, P. (2017). The literature review of technology adoption models and theories for the novelty technology. *JISTEM-Journal of Information Systems and Technology Management, 14*(1), 21-38.Available at: https://doi.org/10.4301/s1807-17752017000100002.

Lauermann, F., & König, J. (2016). Teachers' professional competence and wellbeing: Understanding the links between general pedagogical knowledge self-efficacy and burnout. *Learning and Instruction, 100*(45), 9-19.Available at: https://doi.org/10.1016/j.learninstruc.2016.06.006.

Mois, G., & Beer, J. M. (2020). Robotics to support aging in place. In living with robots (pp. 49-74). Cambridge: Academic Press.

Moslehpour, M., Pham, V. K., Wong, W.-K., & Bilgiçli, İ. (2018). E-purchase intention of Taiwanese consumers: Sustainable mediation of perceived usefulness and perceived ease of use. *Sustainability, 10*(1), 1-17.Available at: https://doi.org/10.3390/su10010234.

Mulyana, M., Din, M., Mustamin, S., Amir, A. M., Karim, F., & Betty, B. (2022). Local government own-source revenue and general allocation funds on capital expenditure: Economic growth as moderating variable. *Arthatama, 6*(1), 44-54.

Nugroho, A. H., Bakar, A., & Ali, A. (2017). Analysis of technology acceptance model: Case study of Traveloka. *Arthatama, 1*(1), 27-34.

Ozturk, A. B., Bilgihan, A., Nusair, K., & Okumus, F. (2016). What keeps the mobile hotel booking users loyal? Investigating the roles of self-efficacy compatibility perceived ease of use and perceived convenience. *International Journal of Information Management, 36*(6), 1350-1359.Available at: https://doi.org/10.1016/j.ijinfomgt.2016.04.005.

Pudjiarti, E., Lisdiyono, E., & Werdiningsih, R. (2022). Knowledge management to develop comprehensive networking of university-industry collaboration in technology and innovation performance. *International Journal of Data and Network Science, 6*(2), 461-468.Available at: https://doi.org/10.5267/j.ijdns.2021.12.008.

Rao, S. R., DesRoches, C. M., Donelan, K., Campbell, E. G., Miralles, P. D., & Jha, A. K. (2011). Electronic health records in small physician practices: Availability use and perceived benefits. *Journal of the American Medical Informatics Association, 18*(3), 271-275.Available at: https://doi.org/10.1136/amiajnl-2010-000010.

Rashid, T., & Asghar, H. M. (2016). Technology use self-directed learning student engagement and academic performance: Examining the interrelations. *Computers in Human Behavior, 100*(63), 604-612.Available at: https://doi.org/10.1016/j.chb.2016.05.084.

Ryan, C., & Rao, U. (2008). Holiday users of the internet—ease of use functionality and novelty. *International Journal of Tourism Research, 10*(4), 329-339.Available at: https://doi.org/10.1002/jtr.660.

Schnall, R., Higgins, T., Brown, W., Carballo-Dieguez, A., & Bakken, S. (2015). Trust perceived risk perceived ease of use and perceived usefulness as factors related to m-health technology use. *Studies in Health Technology and Informatics, 216*(2015), 467–471.

Shank, D. B., Wright, D., Lulham, R., & Thurgood, C. (2021). Knowledge perceived benefits adoption and use of smart home products. *International Journal of Human–Computer Interaction, 37*(10), 922-937.Available at: https://doi.org/10.1080/10447318.2020.1857135.

Sovacool, B. K., & Del Rio, D. D. F. (2020). Smart home technologies in Europe: A critical review of concepts benefits risks and policies. *Renewable and Sustainable Energy Reviews, 120,* 109663.Available at: https://doi.org/10.1016/j.rser.2019.109663.

Tandon, U., Kiran, R., & Sah, A. N. (2018). The influence of website functionality drivers and perceived risk on customer satisfaction in online shopping: An emerging economy case. *Information Systems and e-Business Management, 16*(1), 57-91.Available at: https://doi.org/10.1007/s10257-017-0341-3.

Totanan, C. (2022). Is google classroom zoom and WhatsApp effective for accounting students during the COVID-19 pandemic? *Journal of Education for Business,* 1-7.Available at: https://doi.org/10.1080/08832323.2021.2023853.

Wijiastuti, T. N., & Nurhayati, S. (2021). The effectiveness of discovery blended learning on concept understanding and student motivation. *Research Horizon, 1*(4), 150-156.Available at: https://doi.org/10.54518/rh.1.4.2021.150-156.

Wilson, C., Hargreaves, T., & Hauxwell-Baldwin, R. (2017). Benefits and risks of smart home technologies. *Energy Policy, 103*(C), 72-83.Available at: https://doi.org/10.1016/j.enpol.2016.12.047.

Xu, X., Wang, J., Peng, H., & Wu, R. (2019). Prediction of academic performance associated with internet usage behaviors using machine learning algorithms. *Computers in Human Behavior, 98,* 166-173.Available at: https://doi.org/10.1016/j.chb.2019.04.015.

Yu, J., Lee, H., Ha, I., & Zo, H. (2017). User acceptance of media tablets: An empirical examination of perceived value. *Telematics and Informatics, 34*(4), 206-223.Available at: https://doi.org/10.1016/j.tele.2015.11.004.

Ziefle, M., Halbey, J., & Kowalewski, S. (2016). *Users' willingness to share data on the internet: Perceived benefits and caveats.* Paper presented at the Proceedings of the International Conference on Internet of Things and Big Data (IoTBD 2016), pp. 255-265.