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Modelling E-Government Maturity Determinants at the Local Level in Indonesia Using Technology-Organization-Environment Framework

Torontuan Keban Yeremias[1], Dian Cahyadi[2], Achmad Djunaedi[3]
[1]Department of Public Policy and Management, Faculty of Social and Political Sciences, Universitas Gadjah Mada, Indonesia.
[2]The Graduate School of Universitas Gadjah Mada, Indonesia.
(Corresponding author: diancahyadi86@mail.ugm.ac.id)
[3]Department of Architecture and Planning Engineering, Faculty of Geography, Universitas Gadjah Mada, Indonesia.

Abstract

Local governments in Indonesia have adopted e-government, but the maturity has not met the expected target. The distribution of the achievement of the SPBE index (as a representation of e-government maturity in the context of Indonesia) with a bare minimum "Good" predicate centered on the island of Java raises questions regarding the determinants of success. Existing studies and models on the determinants of e-government maturity mainly focus on local governments in developed countries. This study aims to explore the determinants in the context of local government in developing countries by proposing a new model using the Technology-Organization-Environment (TOE) Framework and assessing the model. The model comprises eight determinants reflecting three variables: technology, organisation, and environment, which can influence the level of e-government maturity in Indonesia. The assessment applies the PLS-SEM multivariate analysis method involving 383 district/city governments in Indonesia in 2021. The results show that the proposed model has adequate validity and reliability, indicating that technology factors (technology and electricity infrastructure), organisational factors (innovative, finance and HR capacity), and environmental factors (human capital, human development, and community welfare) have a significant positive effect on e-government maturity. However, the assessment shows that the model quality measurement is only 31.9% accurate, which is considered weak. Model refinement by strengthening the organisational and environmental variables is needed, and fit-model testing is suggested for further research.

Keywords:
digital government; digital transformation; public policy; SPBE

Introduction

The Industrial Revolution 4.0 has significantly impacted various sectors, including the governments. Such development of information technology has encouraged and raised public demands for the government to transform and provide better services. This transformation in service provision and all aspects of governance by utilising information technology is often termed "*e-government*."

The initiatives of e-government in Indonesia have been implemented since 2003 and were reinstated in 2018 by the Presidential Regulation of the Republic of Indonesia Number 95 of 2018 concerning Electronic-Based Government Systems (SPBE), which aims to create quality and trusted public services and clean governance that is effective, transparent, and accountable. This Presidential Regulation defines SPBE as the "*administration of government that utilises information and communication technology to provide services to SPBE users*."

Accordingly, a 2022 United Nations (UN) survey shows Indonesia's e-government

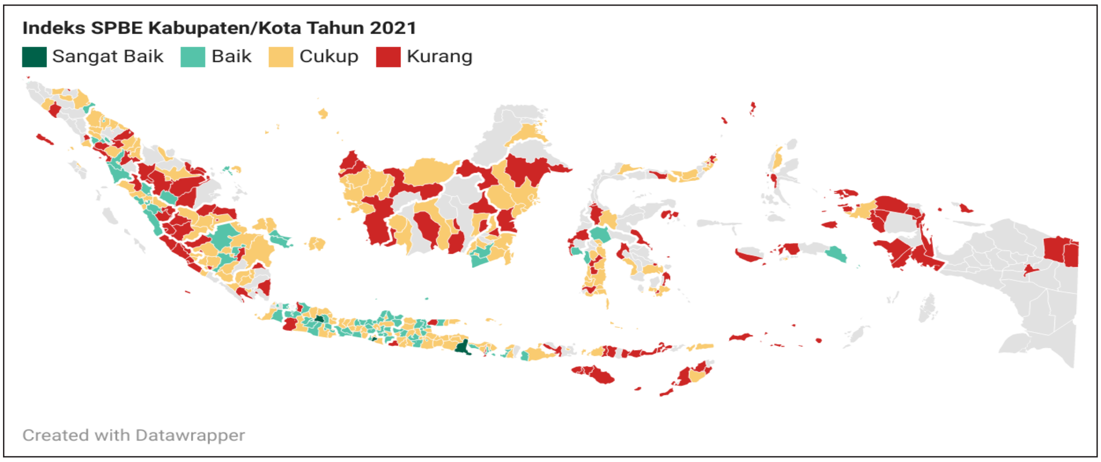

Figure 1. Distribution Map of Achievements of the SPBE Index by Category in 2021
Source: MenPAN RB (2021), processed by researchers

development is ranked 77th out of 193 countries worldwide. This ranking has increased from previous years, when Indonesia was ranked 88th in 2020, 107th in 2018, and 116th in 2016. This achievement is attributable to the various efforts made by the Indonesian government in the last 18 years.

Nonetheless, the achievement of e-government at the local government level in Indonesia has not reached the expected target. The results of the SPBE evaluation 2021, carried out on 391 district/city governments in Indonesia, showed that the SPBE predicate with a minimum category of "Good" only reached 24%, below the expected target of 30%. Furthermore, the distribution map of the SPBE achievements shows that the "Good" and "Very Good" predicates are concentrated on Java Island, parts of Sumatra Island, and only a few in other regions (Figure 1). This uneven distribution raises questions about the critical success factors.

Past studies have discussed the determinants of e-government success, including technological infrastructure and Internet use (Das et al., 2017; Ifinedo, 2011; Krishnan et al., 2017; Larosiliere & Carter, 2016a; Lee et al., 2011; Pudjianto et al., 2011; Serrano-Cinca et al., 2009; Stier, 2015), innovative capacity (Ifinedo, 2011), organisational size and financial resources (Serrano-Cinca et al., 2009), effectiveness and efficiency (Larosiliere & Carter, 2016a; Stier, 2015), population and density level (Budding et al., 2018; Frías-Aceituno et al., 2014; Ingrams et al., 2020; A. Manoharan, 2013; Stier, 2015), welfare (Ifinedo, 2011; Ingrams et al., 2020; Larosiliere & Carter, 2016a; Serrano-Cinca et al., 2009; Singh et al., 2007), community education level (Das et al., 2017; Ifinedo, 2011; Krishnan et al., 2017; Larosiliere & Carter, 2016a; Lee et al., 2011), capital and human development (Stier, 2015). Other factors have been confirmed to positively influence the level of transparency, democracy and law enforcement, political factors, and competition. These studies' context is the development of e-government at the country level (Das et al., 2017; Ifinedo, 2011; Krishnan et al., 2017; Larosiliere & Carter, 2016a; Lee et al., 2011; Singh et al., 2007; Stier, 2015) and the local level in developed countries (Budding et al., 2018; Frías-Aceituno et al., 2014; A. Manoharan, 2013; Serrano-Cinca et al., 2009). Meanwhile, research on the determinants of e-government maturity at the local level in developing countries has not been conducted. In Indonesia, research has only explored e-government at the agency level (Indraswati & Akram, 2019; Pudjianto et al., 2011). Given the differences in characteristics between e-government maturity at a country level and local level, as well as between developed and developing countries, it is necessary to carry out quantitative research that develops models appropriate to the context of e-government development at the local government level in developing countries, especially in Indonesia.

This study explores the factors that influence the level of e-government development at the local level in developing countries by adopting the Technology-Organization-Environment (TOE) framework and assessing it in local governments in Indonesia. The level of e-government development is generally measured by assessing the level of maturity, which, in the context of local government in Indonesia, is manifested in the SPBE index.

Literature Review

E-government essentially refers to digital transformation by utilising information and communication technology by the government via the Internet and other digital technologies (United Nations, 2020) to achieve specific goals (Nam, 2019), including providing information and services and interacting electronically (Sharma, 2006) with all relevant stakeholders. Meanwhile, e-government maturity is the extent to which the government has represented itself online (Singh et al., 2007) and implemented ICT in government. Maturity is assessed based on the stages that have been achieved, namely emerging, enhanced, interactive, transactional, and seamless/connected (United Nations, 2008; United Nations & ASPA, 2002). The higher the implementation stage, the greater the maturity level is.

In Indonesia, e-government maturity is assessed using the SPBE index. The SPBE maturity level assessment is carried out in four domains consisting of eight aspects and 47 indicators with their respective weights. The maturity level is formulated into five levels for process capability: piloted, managed, defined, measurable, and optimum; and five levels for service capability: information, interaction, transaction, collaboration and optimum.

Various theories and frameworks have been applied in research related to e-government. One relevant framework is the TOE framework introduced by Tornatzky and Fleischer (1990) in their book "*The Processes of Technological Innovation*." This uses the TOE framework, following studies by Krishnan et al. (2013, 2017), Hanum et al. (2020), Defitri et al. (2020), and Pudjianto et al. (2011). In addition, the TOE framework was chosen based on the understanding that e-government is essentially a continuous innovation process involving information technology, aligned with the stages of the technological innovation described by Tornatzky and Fleischer (1990) as the theory's originators. The TOE framework describes the general factors that influence the process of technological innovation and explains the relationship between the factors at a macro level, which is the focus of this study. The weakness can be overcome using multiple indicators in the SEM-PLS analysis method adopted in this study.

Tornatzky and Fleischer (1990) explained that technological innovation is a continuous process divided into two stages: the development stage and the implementation stage, which occur at all levels of the social hierarchy, ranging from the individual to the societal level, one of which is the organisational level (Tornatzky & Fleischer, 1990, p. 33). The TOE framework postulates that the decision-making of adopting and implementing technological innovations at the organisational level is influenced by three elements: technology, organisation and environment (Baker, 2012), whose relationships are shown in Figure 2.

Based on the literature review and considering the characteristic differences between national and local governments, as well as between local governments in developed and developing countries, the determinants of e-government maturity based on the TOE framework are formulated in Table 1.

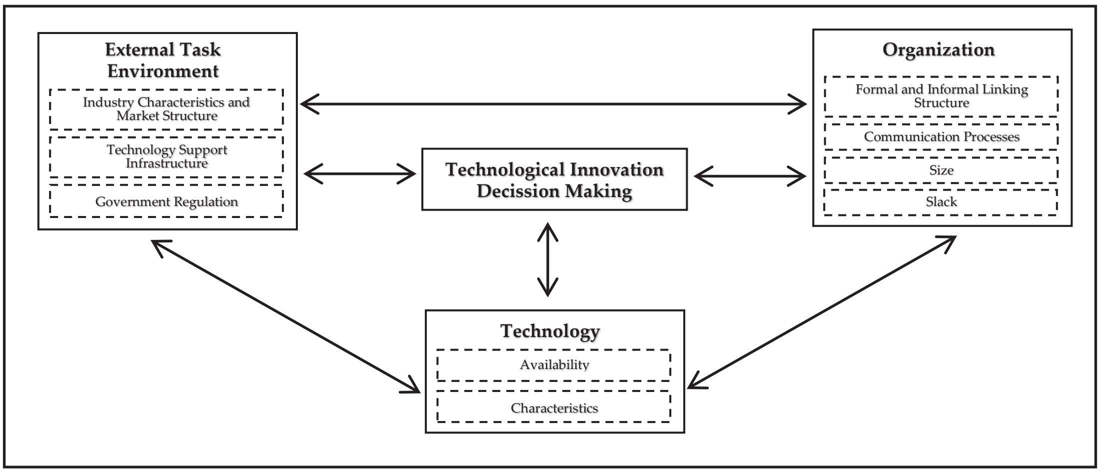

Figure 2. TOE Framework

Source: Tornatzky and Fleischer (1990)

Table 1.
Determinants of e-Government Maturity in the TOE Framework

No	Determinant	Purpose	Literature
Technology			
1	Internet Infrastructure	Knowing the level of availability of Internet and electricity infrastructure	(Das et al., 2017; Krishnan et al., 2017)
2	Electrical Infrastructure		
Organisation			
3	Innovative Capacity	Measure the level and innovative culture of local government	(Ifinedo, 2011)
4	Financial Capacity	Measuring the availability of funds owned by local governments	(Serrano-Cinca et al., 2009)
5	HR capacity	Measuring the level of competence of employees	(A. Manoharan, 2013)
Environment			
6	Human Capital	Measuring the level of community education	(Das et al., 2017; Krishnan et al., 2017)
7	Human Development	Measuring people's quality of life	(Stier, 2015)
8	Public welfare	Measures the size of the regional economy per unit of population in an area	(Ifinedo, 2011; Ingrams et al., 2020; Larosiliere & Carter, 2016a; Serrano-Cinca et al., 2009; Singh et al., 2007)

Source: Various sources cited in this study's theoretical framework

The technological factor is the most dominant in influencing e-government. In past research, technological factors are represented by the Internet infrastructure. However, in the context of local governments in developing countries, the availability of such infrastructure needs to be supported by the availability of supporting infrastructure, such as electricity. Internet infrastructure without the support of electricity will not be functional. In Indonesia, the supporting infrastructure is not distributed evenly across local government offices. Hence, we consider this indicator to be part of the technological factor. Thus, hypothesis 1 is formulated as follows:

H 1: *The availability of technology, including its supporting infrastructure, has a significant positive effect on the e-government maturity level at local governments in Indonesia.*

Past research has also shown that the effect of organisational factors at the country level, represented by the governance index, is insignificant (Das et al., 2017; Krishnan et al., 2017; Singh et al., 2007). By contrast, innovative capacity (Ifinedo, 2011), organisational opportunities or financial capacity (Serrano-Cinca et al., 2009), and human resource capacity or educational level (A. Manoharan, 2013) positively affect e-government maturity. Even though past studies have shown significant effects of such determinants (Frías-Aceituno et al., 2014; A. P. Manoharan et al., 2017), the same effects on local governments in developing countries have yet to be discovered, given the different financial capacities in each region.

More specifically, past studies have shown that financial capacity allows local government organisations to be more flexible in developing the e-government program. Adequate funding means that the needs for other main government programs have also been fulfilled. Likewise, the availability of employees, especially those with higher education, can contribute their knowledge and experience to developing better e-government. Lastly, the organisation's innovative culture can also accelerate the achievement of e-government maturity. In other words, the combination of various internal organisational factors influences the success of e-government development. Thus, hypothesis 2 is formulated as follows:

H_2: *Innovative capacity, finance and human resources of the organisation have a significant positive effect on the e-government maturity level at local governments in Indonesia.*

Next, environmental determinants such as population (Budding et al., 2018; Frías-Aceituno et al., 2014; Ingrams et al., 2020; A. Manoharan, 2013; Stier, 2015), community welfare (Ifinedo, 2011; Ingrams et al., 2020; Larosiliere & Carter, 2016a; Serrano-Cinca et al., 2009; Singh et al., 2007), human development (Stier, 2015), and human capital (Das et al., 2017; Ifinedo, 2011; Krishnan et al., 2017; Larosiliere & Carter, 2016a; Lee et al., 2011) have been confirmed to affect e-government maturity significantly. Meanwhile, other environmental factors, such as law enforcement (Ifinedo, 2011), democracy (Stier, 2015), political factors (Serrano-Cinca et al., 2009), and firm activities (A. Manoharan, 2013; Serrano-Cinca et al., 2009), are irrelevant when applied in the context of local government in developing countries, given the similar characteristics of all local governments. In contrast, when combined, the population factor is inversely correlated with human welfare measured by GRDP per capita.

The general public's level of education increases the expectations of their government, encouraging improvements in government programs and services. It also affects the main actors who play a role in the government organisation to improve the quality of services through e-government. Human development and community welfare will also encourage the government to improve the quality of its services. Welfare and high quality of life mean that people have fulfilled their primary needs, so they will have more time to be involved in developing e-government services. Thus, hypothesis 3 is formulated as follows:

H_3: *Human capital, human development, and social welfare are environmental factors that have a significant positive effect on the e-government maturity level of local governments in Indonesia.*

Methods

We propose a determinants model of e-government maturity at the local level in developing countries with a specific case in Indonesia, as shown in Figure 3. The exogenous latent variables in the model consist of technological, organisational and environmental variables. The indicators of the Internet (T1_INET) and electricity infrastructure (T2_ELX) reflect the technology variable. The organisational variable is indicated by innovative capacity (O1_INOV), financial capacity (O2_FIN) and human

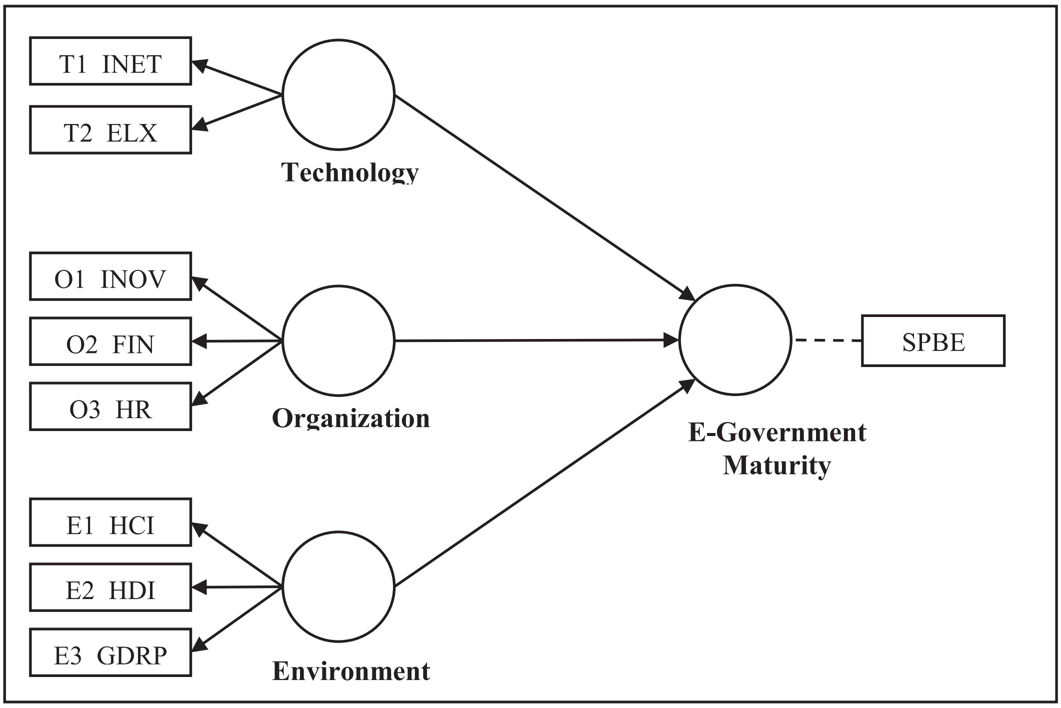

Figure 3. Research Model

Source: The TOE Framework, processed by authors

resources capacity (O3_HR). Meanwhile, the environmental variable is indicated by human capital (E1_HCI), human development (E2_HDI) and community welfare (E3_GRDP).

The endogenous variable in this study is e-government maturity (EGOV), represented by the SPBE index value. The SPBE index uses a composite index, a combination of indexes in the SPBE policy, governance, management, and service domains.

To test the hypothesis, we use secondary data from the official website. We have also requested related data and documents from various government agencies. Data related to internet infrastructure (T1_INET) and electricity (T2_ELX) were obtained from requests and purchases of 2021 village potential survey microdata from Statistics Indonesia (BPS) through the SILASTIK application. The data requested consists of district names, sub-districts, village codes, and mobile Internet signals in most areas in villages and sub-districts with a value of 1 for villages with 4G/LTE and 3G/H/H+/EVDO Internet and 0 for others. This value describes villages that have a minimum 3G Internet signal, which is then added up and divided by the number of all villages for each district/city multiplied by 100% so that the percentage value of villages with at least 3G cellular Internet access is obtained for each district/city. Electricity infrastructure is obtained by calculating the electrification ratio, which is also obtained from SILASTIK by calculating the number of families of state-owned electricity company (PLN) customers divided by the total number of families in each district/city and multiplied by 100%. These two indicators reflect this research model's Technology (T) variable.

The organisational (O) variable is indicated by innovative capacity, finance and human resources. Organisational innovative capacity (O1_INOV) is measured using the Government Innovation Index, which originates from Minister of Home Affairs Decree Number 002.6-5848 of 2021 concerning the Provincial, District and City Regional Innovation Index of 2021. Financial capacity

(O2_FIN) is measured using the realised value of local budget revenues in 2021, with data obtained from the portal of APBD Postur belonging to the Director General of Fiscal Balance, Ministry of Finance, and presented in billions of rupiah. Human resources capacity (O3_HR) is measured using the number of civil servants with a high education level in 2021, with data from "Regency/City in Figure 2022".

The environmental (E) variable is indicated by human capital, human development, and social welfare. Human capital (E1_HCI) is measured by the human capital index processed from BPS data with the formula: 1/3 × z-score literacy rate + 2/9 × z-score gross enrollment ratio + 2/9 × z-score average length of school + 2/9 × z-score expected years of school which is then carried out the data normalisation process. Human development (E2_HDI) is measured using the 2021 district/city human development index obtained from the BPS website, which is calculated from three dimensions: education, health and viability of living. Community welfare (E3_GRDP) is measured by the 2021 GRDP per capita value obtained from the BPS website. Meanwhile, e-government maturity is measured by the SPBE Index for 2021 obtained from the Ministry of State Empowerment and Bureaucratic Reform.

The collected data, which is formed in a dataset, was used in data analysis with 383 local governments after the extreme outliers were cleaned. Data analysis was performed using the Partial Least Squares – Structural Equation Modeling (PLS-SEM) method using the Smart PLS 4.0 application. Data analysis went through two stages: the assessment of the measurement model and the assessment of the structural model.

In the measurement model assessment, the model is tested for its validity and reliability. Convergent validity test is done by calculating the value of outer loading and average variance extracted (AVE). Indicators with an outer loading value above 0.708 and an AVE value above 0.500 are considered valid. An analysis of the impact of removing indicators on data reliability is required for outer loading values above 0.400 and below 0.700. Meanwhile, indicators with outer loading values below 0.400 must be removed from the variable (J. Hair et al., 2017, p. 129). Discriminant validity is assessed by calculating the cross-loading value of the research instrument. If the outer loading value of the instrument is more significant than its cross-loading, it is considered valid (J. Hair et al., 2017). In addition, discriminant validity can also be calculated by the Heterotrait-Monotrait (HTMT) value, which is considered valid with a maximum limit of 0.900 (Henseler et al., 2015). Meanwhile, the reliability test was carried out by calculating the composite reliability and Cronbach's alpha, with a value greater than 0.600 considered reliable. However, if the value exceeds 0.900 or even 0.950, the indicator measures the same phenomenon, which is considered unreliable (J. Hair et al., 2017). Models that meet the criteria in this assessment can continue to the structural model assessment.

A structural model assessment was carried out to determine the significance level of the path coefficients in the model. The direction of the influence is declared positive if it produces a path coefficient greater than zero ($\beta > 0$). Meanwhile, the effect is stated to be significant if the $t_{stat} > t_{table}$. For 383 samples with a minimum significance level of 0.050, a state that exceeds 1.290 (one-tailed test) is required. Furthermore, the quality of the model was tested by calculating the coefficient of determination value (R^2). The R^2 value indicates how much power all exogenous variables have in predicting endogenous variables. This value can also indicate how well the path model is assessed based on the data obtained, termed "*in-sample predictive power*", (Sarstedt et al., 2014) and classified as weak, medium, and robust at values of 0.250, 0.500 and 0.750, respectively (J. F. Hair et al., 2011). However,

Table 2.
Descriptive Statistics (n=383)

No	Indicator	Means	Median	Min	Max	St. Dev	Kurtosis	Skewness
1	T1_INET	0.784	0.830	0.100	1.000	0.185	0.129	-0.877
2	T2_ELX	0.945	1.000	0.130	1.000	0.134	11.025*	-3.244
3	O1_INOV	39.017	43.040	0.080	84.190	17.153	-0.542	-0.565
4	O2_FIN	1,697.458	1,332.350	309.660	8,326.880	1,079.928	6.347*	2.135
5	O3_HR	3,642.209	3,148.000	282.000	10,719.000	1,908.429	0.764	1.038
6	E1_HCI	0.783	0.780	0.500	1.000	0.071	0.453	-0.025
7	E2_HDI	71.338	70.490	57.030	87.180	5,196	0,043	0.480
8	E3_GRDP	54.656	41.970	12,280	491.270	48,491	25.048*	4.159
9	EGOV	2.167	2.190	1.000	3.620	0.591	-0.538	-0.081

Source: Output from SmartPLS 4.0, processed by authors
*Note: *Indicators with normality problem*

before these tests, all of the variables in the model must be clear from data collinearity problems at the construct level by calculating the variance inflation factors value in the VIF ≤0.200 or VIF ≥5.000 range.

Results

Descriptive statistics

Table 2 represents the descriptive statistics of the data. All data (n=383) for each indicator has been verified to ensure its correctness, and extreme outliers that might affect the analysis's results have been removed. Because the PLS-SEM analytical method does not require a normality assumption, several identified indicators with this problem (T2_ELX, O2_FIN, E3_GRDP) are maintained.

Measurement Model Assessment

The assessment of the measurement model is carried out by testing the validity and reliability of the data. Table 3 shows the results of the validity test, while Table 4 shows the results of the reliability test. The technology (T) variable, as indicated by Internet infrastructure (T1_INET) and electricity infrastructure (T2_ELX), has met the convergent validity. The outer loading values for each indicator were 0.941 and 0.860 or greater than the minimum threshold of 0.7. In addition, the AVE value of the two indicators (0.812) is greater than

Table 3.
Validity Test Results

Variables and Indicators	Validity Test		
	Convergent		Discriminant
	Outer Loadings	AVE	Cross Loading & HTML
	>0.700	>0.500	
Technology (T)			
1 T1_INET	0.941	0.812	Fulfiled
2 T2_ELEK	0.860		
Organisation (O)			
3 O1_INOV	0.615 *		
4 O2_KEU	0.895	0.664	Fulfiled
5 O3_SDM	0.902		
Environment (E)			
6 E 1_IMM	0.810		
7 E 2_IPM	0.992	0.623	Fulfiled
8 E 3_GRDP	0.480 *		
Conclusion	**Fulfilled**		**Fulfilled**

Source: Output from SmartPLS 4.0, processed by authors
*Note: *) Assessing the impact of removing indicators produces a composite reliability value above the maximum threshold of 0.900*

the minimum threshold of 0.500, so the two indicators can represent technology variables at 81.2% of all determinants.

Organisation (O) variables, as indicated by innovative capacity (O1_INOV), financial capacity (O2_FIN), and human resources capacity (O3_HR), generally meet the convergent validity. This is shown by the AVE value of the three indicators of 0.664 (>0.500).

Even though the innovative capacity indicator (O1_INOV) has an outer loading value below 0.700, the assessment of removing the impact of this indicator produces a composite reliability value above 0.900 (not reliable), and this indicator must be retained in the model. From these results, the three indicators can validly represent organisational variables at 66.4%.

Environment (E) variables, as indicated by human capital (E1_HCI), human development (E2_HDI), and community welfare (E3_GRDP), generally meet the convergent validity. This is shown by the AVE value of 0.623, above the minimum threshold (>0.500). Even though the community welfare indicator (E3_GRDP) has an outer loading value below 0.700, the assessment of removing the impact of this indicator produces a composite reliability value above 0.900 (not reliable). Thus, the indicator must be retained in the model. These results concluded that the three indicators can represent environmental variables at 62.3%.

Table 4.
Reliability Test Results

No	Latent Variable	Reliability Internal Consistency: Composite Reliability	Reliability Internal Consistency: Cronbach's Alpha
		0.600–0.900	0.600–0.900
1	Technology (T)	0.896	0.777
2	Organisation (O)	0.852	0.728
3	Environment (E)	0.822	0.733
Conclusion		Fulfilled	

Source: Output from SmartPLS 4.0, processed by authors

The reliability assessment results (Table 4) showed that the composite reliability and Cronbach's alpha of all variables are in the ideal values, namely between 0.700 and 0.900. The composite reliability value of the technology variable is 0.896, the organisation variable is 0.852, and the environment variable is 0.822. The values of Cronbach's alpha for these three variables are 0.777, 0.728, and 0.733. Thus, it can be concluded that all indicators are consistently reliable in measuring their latent variables.

Based on the results of the measurement model assessment, it was concluded that all indicators representing the latent variables in the model are sufficiently valid and reliable and could proceed to the structural model assessment.

Structural Model Assessment and Hypothesis Testing

Table 5 presents the results of the structural model assessment. The results of the collinearity test show that the variables of technology (T), organisation (O) and environment (E) do not have collinearity problems at the construct level with respective values of 1.577, 1.170 and 1.405 (<0.5). Based on these results, it was concluded that the path coefficient significance test could proceed to the proposed model.

The results of the path coefficient significance test show that the technology (T) variable has a path coefficient on e-government maturity (EGOV) of 0.262 (t_{stat}= 5.051) with a significance level of 0.001 (n=383 with one-tailed test). This confirms

Table 5.
Significance Test Results for Path Coefficients and Hypotheses

Hypothesis and Construct	Collinearity (VIF)	Path Coefficient Significance: β	Path Coefficient Significance: t_{stat}	Conclusion
	< 5	>0	> 1,290	
H_1 : T → EGOV	1,577	0.262 *	5,051	not rejected
H_2 : O → EGOV	1,170	0.364 *	8,687	not rejected
H_3 : E → EGOV	1.405	0.089 **	2,142	not rejected

Source: Output from SmartPLS 4.0, processed by authors
*Note : * significance level of 0.001 at n=383 (one-tailed test).*
***significance level at 0.05 at n = 383 (one-tailed test).*

that the availability of technology, including its supporting infrastructure, significantly affects the e-government maturity level at local governments in Indonesia (hypothesis 1 is not rejected).

Testing the significance of the path coefficient on the organisation (O) variable on e-government maturity (EGOV) yields a coefficient of 0.364 (t_{stat}=8.687) with a significance level of 0.001 (n = 383 with one-tailed test). This confirms that organisations' innovative, financial, and human resource capacities have a significant positive effect on the e-government maturity level at local governments in Indonesia (hypothesis 2 is not rejected).

Meanwhile, the significance test for the path coefficient of the environment (E) variable has a path coefficient of 0.089 (t_{stat} = 2.142) with a significance level of 0.05 (n = 383 with a one-tailed test). Although the significance level of this variable is lower than the other variables, the assessment also confirms that human capital, human development, and social welfare, all of which are environmental factors, have a significant positive effect on the e-government maturity level at local governments in Indonesia (hypothesis 3 is not rejected).

In addition, the model quality test produces a coefficient of determination of 0.319 (weak category), as shown in Table 5. Organisational variables have the most significant influence on the model, followed by technology and environmental variables. This is indicated by the value of f^2 on each variable of 0.166, 0.064 and 0.008, respectively. With these values, it can be concluded that organisational variables have a moderate influence on the model (>0.150), technology variables have a

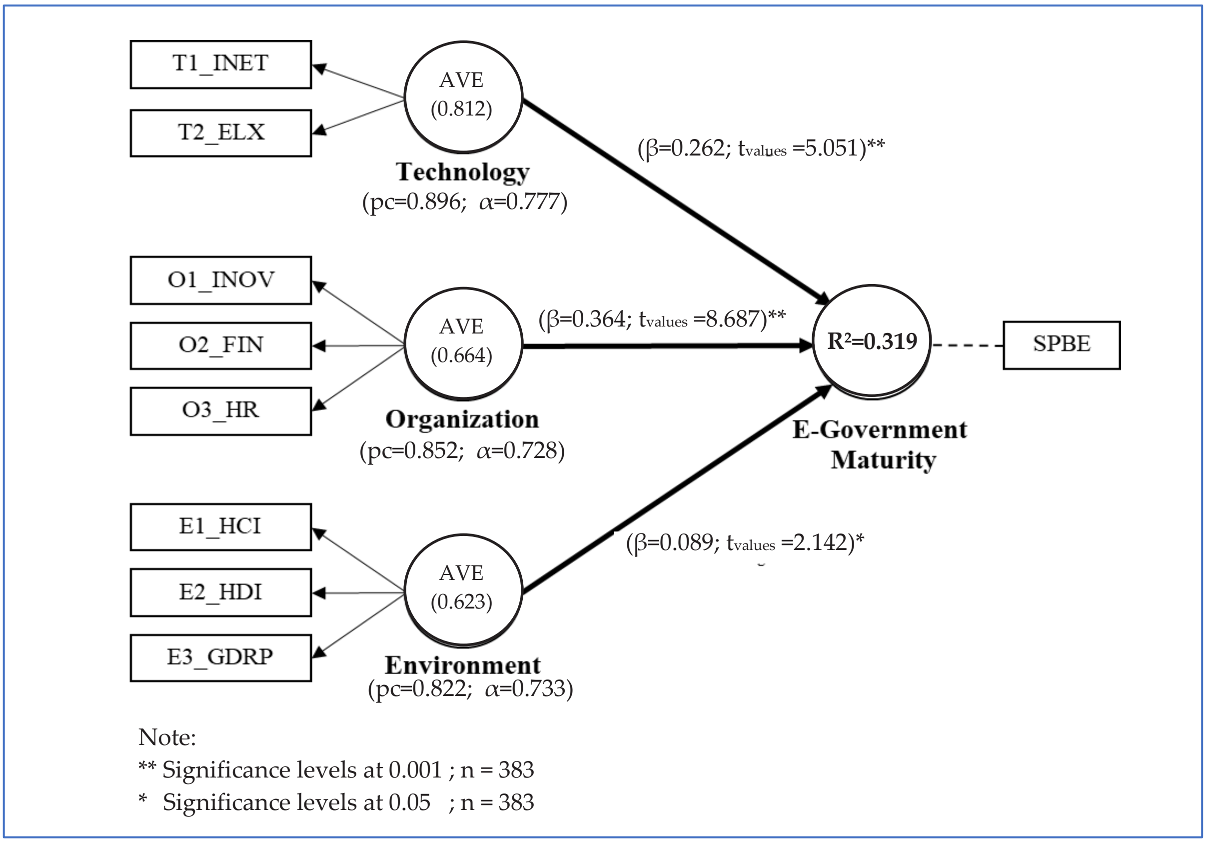

Figure 4. Model Assessment Result

Source: Output from SmartPLS 4.0, processed by author weak influence (> 0.020), and environmental variables have no influence on the model (< 0.020).

Table 6.
Test Results for the Coefficient of Determination (R^2) and Effect Size f^2

Construct	Coefficient of Determination (R^2) Include	Coefficient of Determination (R^2) Exclude	Effect Size f^2
	>0.250	>0.250	>0.020
T → EGOV	0.319 & 0.314 (adj)	0.276	0.064
O → EGOV		0.206	0.166
E → EGOV		0.313	0.008 *)

Output from SmartPLS 4.0, processed by the authors
*Note : *the effect size f^2 is below the threshold of 0.020.*

Discussion

The Assessment of the Model

The assessment results of the technology (T) variables on e-government maturity show a significant effect. The technology variable, with Internet and electricity infrastructure indicators, represents 81.2% of the determinants (AVE=0.812), in line with previous studies (Das et al., 2017; Ifinedo, 2011; Krishnan et al., 2017; Larosiliere & Carter, 2016b; Lee et al., 2011; Serrano-Cinca et al., 2009; Stier, 2015). Meanwhile, the use of electricity infrastructure indicators in the variable shows that the use of Internet infrastructure, especially in developing countries, requires the support of electricity infrastructure to form a technological ecosystem that supports the development of e-government.

Regarding technological variables, Ifinedo (2011) places innovative capacity as part of technological factors in addition to ICT infrastructure and confirms its significant effect on e-government maturity directly. However, that study did not explain the effect of its combination with ICT infrastructure. Contrarily, this study places innovative capacity as part of organisational factors and electricity infrastructure as a factor that supports the technology. The results of the cross-loading analysis show that innovative capacity is more closely correlated with organisational factors than technology. At the same time, power and Internet infrastructure constitute 81.2% of all technology factors, which is satisfactory.

The organisation (O) variables assessment shows a significant positive effect on e-government maturity, with indicators of innovation, finance, and human resources capacity representing 66.4% of the determinants (AVE=0.644). This finding aligns with other studies that confirm the effect of innovative capacity (Ifinedo, 2011), financial resources (Serrano-Cinca et al., 2009), and employee education (A. Manoharan, 2013) on e-government. This finding has also confirmed Krishnan et al. (2017), which places governance as the representation of organisational variables and generates insignificant results (Das et al., 2017; Singh et al., 2007). Thus, it can be concluded that the development of e-government is strongly influenced by various interconnected factors within the organisation, including innovative capacity, financial capacity, and human resources capacity, as well as 33.6% of other factors not covered in this study.

The assessment of environment (E) variables shows a significant positive effect on e-government maturity but with the lowest significance level. In addition, indicators of human capital, human development, and social welfare only represent 62.3% of the determinants (AVE=0.623). This finding is in line with Stier (2015), who revealed the influence of human development on e-government. This finding also confirms the significant influence of human capital (Ifinedo, 2011; Krishnan et al., 2017; Larosiliere & Carter, 2016b; Lee et al., 2011) and the insignificant impact of human capital on e-government (Das et al., 2017; Singh et al., 2007).

As a result, the community welfare indicator, as measured by GRDP per capita, has the smallest contribution compared to the other two indicators. This indicator has an outer loading value below the generally supported minimum limit (0.480 from 0.707). This finding differs from other studies, where more research confirms the significant effect of GRDP per capita on e-government maturity (Ifinedo, 2011; Ingrams et al., 2020; Larosiliere & Carter, 2016b; Serrano-Cinca et al., 2009; Singh et al., 2007) than those that reject it (Budding et al., 2018; Lee et al., 2011). This indicates that in Indonesia's context, the GRDP per capita level cannot fully reflect the community's welfare, especially in areas with specific characteristics. This indication is strengthened by the assessment results showing that the human development index (HDI) contributes most to environmental variables.

HDI is an indicator of quality of life, encompassing education, health, and liveability. The level of liveability is measured by the expenditure per capita, which is calculated based on each region's gross national income (GNI) per capita. GNI per capita is used to calculate HDI because it better reflects people's income than the GRDP per capita value (BPS, n.d.).

Under ideal conditions, a high GRDP per capita should improve the community's quality of life, as indicated by a high HDI. Still, this condition does not occur in certain areas. Therefore, it can be concluded that economic conditions may not impact the welfare of its citizens, i.e., one of the determinants of the development of e-government. Nonetheless, the government needs to focus more on areas with the abovementioned characteristics. Policies that ensure the wealth of a region can be proportionately distributed to the people are needed.

In sum, the development of e-government requires supporting external environmental conditions, which include the general public's high level of education or human capital, human development, and social welfare.

Model Reviews

Although the three variables and their indicators have been confirmed to significantly positively affect e-government maturity, the results measuring the model's quality show a weak explanatory power level (R^2=0.319). This shows that the overall model only accounts for 31.9% of the factors affecting e-government maturity, mainly due to the low representation of the indicators of organisational and environmental variables (66.4% and 62.3%).

The low coefficient of determination is partly due to the low contribution of environmental variables. This can be seen from the assessment of the effect size (f^2 = 0,008) of these variables to the level of explanatory power. Moreover, the absence of environmental variables in the model is relatively insignificant to the model. This finding is reasonable considering the context. The development of local e-government in Indonesia still focuses on using an internal information system that the government developed. The development of the internal information system indicates an early stage of e-government development and represents only one of its scopes. E-government has a broader scope, including the use of social media (Alryalat et al., 2017; 2018), advanced digital technologies such as big data (Anshari & Lim, 2017), the Internet of Things (Papadopoulou et al., 2020), cloud computing (Adu et al., 2016), machine learning (Alexopoulos et al., 2019), community involvement in government or e-participation (Krishnan et al., 2013; Ndiege, 2020), digital democracy (Roy, 2019) and more.

Nevertheless, these findings are still statistically acceptable in the social field research, which is supported by similar studies at the local level in developed countries, which also show low yield, such as by Frías-Aceituno et al. (2014) with a value of 25%, Budding et al. (2018) with a score of 40%, 39.1% and 37.1% in 2014, 2015 and 2016 analysis respectively, and A. Manoharan (2013) with a score of (45.7%).

Referring to the results of the country-level research model, which produces an explanatory power value of 63% (Krishnan et al., 2017), we can confirm the initial assumption of the difference in the local e-government characteristics and differences in the determinants. The development of e-government in the local government is influenced by factors other than what has been revealed in this study, including political and policy factors. The development of e-government in local governments is typically mandatory based on e-government policies set by the central government. Hence, the success of its development cannot be separated from the role of the central government and the local government's response to the policies. Therefore, the determinants of policy implementation, such as disposition, communication, resources and bureaucratic structure (Edwards, 1980) , also greatly influence the development of e-government. This indicates a direction for further research.

E-Government Evolution and Its Determinants

The evolution of e-government is generally long-term and consists of several phases. Janowski (2015) divided this phase into four stages: digitisation, transformation, engagement, and contextualisation. Digitisation is characterised by using ICT without any internal government transformation, also termed "*technology in government*". Transformation is characterised by transforming service business processes within the internal government by applying digital technology, also termed "*electronic government*". Engagement is characterised by the use of digital technology by the government in establishing relationships with other stakeholders to increase access and convenience in providing services, which is also termed "*electronic governance*". Contextualisation is characterised by the government's efforts to support sustainable development goals involving the broader context in their digital transformation, also termed "*policy-driven electronic governance*".

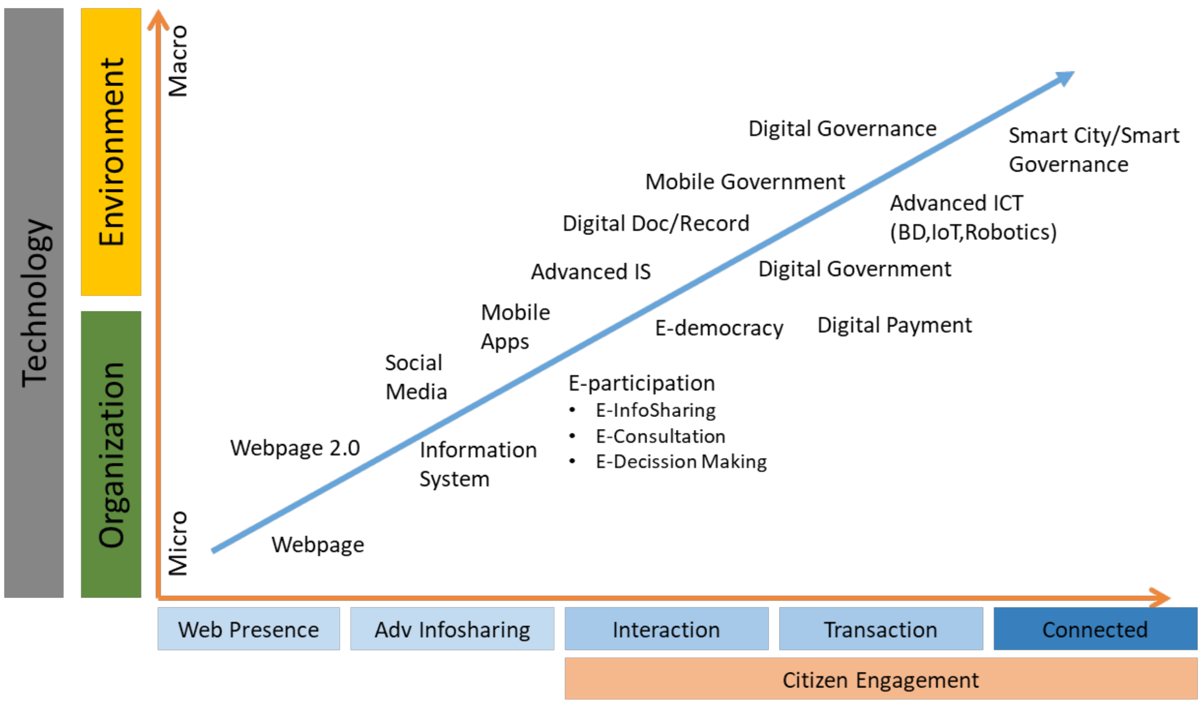

Figure 5.Internet Technology Evolution

Source : Milakovich (2021, p. 33)

Another stage is called "*smart digital governance*", namely "expanding the use of ICT as a strategy to improve organisational performance using advanced analytical tools" (Milakovich, 2021, p. 17). The stage uses sophisticated networks, systems and technologies (among which are artificial intelligence technologies, blockchain, cloud computing, data analytics, machine learning and so on) in good state management. The cooperation of the executive, legislative and judicial functions with experienced professionals is needed at this stage, where a "*smart city*" is one example.

From the stages above, the higher the level of e-government evolution can be realised, and the more sophisticated the technology used, the higher the role and involvement of external environmental factors. In the early stages of e-government evolution, the most dominant influence besides the technological aspect was the organisation of the government itself. In contrast, the environmental aspect only played less and will increase along with the development and evolution of e-government (Milakovich, 2021). E-participation, for example, increases community involvement by providing information-sharing services (e-information), online consultation (e-consultation), and e-decision-making (United Nations, 2003). Its application is not only related to the development of information systems but is also closely related to the citizen's active participation. Whether or not this application is practical is determined by the level of education, digital literacy, and economic and social welfare (Krishnan et al., 2013; Ndiege, 2020).

Limitations and Further Research

This study has several limitations, including using the SPBE index to represent e-government maturity. The SPBE index was explicitly developed for government agencies in Indonesia, so it may be irrelevant when applied to other developing countries. For this reason, e-government maturity, which refers to the local online service index (LOSI) developed by the United Nations (2018), is recommended.

Referring to the model assessment results, the combination of various indicators that reflect the organisational and environmental variables only contributed 66.4% and 62.3%, which implies other determinants not covered in the model. Other organisational and environmental variables determinants can be discovered by examining various e-government studies, including the micro aspects. Several studies have concluded that the implementation of e-government is also influenced by training and employee involvement, system availability, work culture (Alshibly et al., 2016) and IT staff's technical competence (Awaludin, 2019), political factors, and private business activities (Serrano-Cinca et al., 2009). Integrating the macro and micro aspects into a model could be applied in future research. In addition, this study cannot explain each indicator's direct or indirect effect on e-government maturity nor the influence and interaction between each indicator. Therefore, research that develops models for such interactions and their influence on e-government maturity is needed.

The quality of the model in this study has met the minimum statistical requirements in the social sciences, even though the model's explanatory power should be improved by including other appropriate determinants. Another weakness in the model is the problems related to data normality. Although PLS-SEM does not require assumptions, these may drive the low quality of the model. Therefore, further research can focus on strengthening organisational and environmental variables by including other relevant indicators, including factors related to policy implementation such as disposition, communication, resources and bureaucratic structure, as well as overcoming data normality problems and reassessing the model using the CB-SEM method to confirm the theory and achieve model fit.

Conclusion

This study fills the research gap by proposing an e-government maturity determinants model at the local level in developing countries using the TOE framework as a theoretical basis. The model assumes technology (Internet and electricity), organisation (innovative capacity, finance and human resources), and environment (human capital, human development, and social welfare) as determinants of e-government maturity. The test results confirm that maturity is significantly affected by TOE factors.

The results of the model assessment predicted 39.1% of the existing determinants. Similar results have also been shown in several studies at the local government level in developed countries. Meanwhile, the country-level determinants model shows a higher level of prediction, which confirms the initial assumption that the e-government development at the local level is different from the country level.

The low quality of the model is also caused by the low effect of environmental factors, which is reasonable in Indonesia, where e-government development is still at an early stage and focuses on internal users. Development at a higher stage also requires the role of higher environmental factors. Therefore, the government must focus on increasing citizen involvement in developing e-government in Indonesia. In addition, this study also has several limitations that require improvement in future research.

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