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Understanding User Acceptance towards Case Management System: A UTAUT Analysis

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Abstract

To improve the quality of case handling administration, the Indonesian National Police has implemented a technology-based platform, a Case Management System (CMS). This study employs the UTAUT model to examine the factors influencing the interest of Indonesian National Police investigators in using the CMS. Data were collected through an online survey distributed to all investigators. Multivariate analysis using PLS-SEM was conducted to identify and predict the factors significantly influencing user acceptance. The results indicate that government policies and regulations, performance expectancy, and social influence significantly influence behavioral intentions towards the system, whereas effort expectancy does not. Behavioral intentions and facilitating conditions significantly influence system usage behavior. In conclusion, the UTAUT model demonstrates valid and reliable measurements, as well as a good goodness of fit in predicting investigators' interest or intention to use the CMS system, which can be utilized for the development of information systems in government agencies.

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A. Introduction

The Indonesian National Police is a state institution that plays a crucial role in maintaining stability and security in Indonesia. In carrying out its role, Indonesian National Police has the authority to conduct investigations into all forms of criminal acts. To improve the quality of investigation administration and optimize its processes and management, Indonesian National Police uses the Case Management System (CMS).

The Case Management System (CMS) is established as the primary tool in the investigation of criminal acts at various organizational levels of Indonesian National Police, namely at the National Police Headquarters, Regional Police, District Police, and Sector Police levels. Given the significant role of the CMS system, the Criminal Investigation Agency (Bareskrim) of Indonesian National Police has set a target of 90% usage of the CMS system by 2024 [1].

To encourage the use of the CMS system, various efforts have been made by the operational managers of the CMS system, such as conducting training sessions, establishing various government policies and regulations, and even implementing reward and punishment schemes related to user activities in using the system. However, based on evaluation analysis conducted by the division responsible for the operation of the CMS system, there are still users who have never used the system.

Therefore, this study aims to examine the factors that influence the use of the CMS system in Indonesian National Police using the Unified Theory of Acceptance and Use of Technology (UTAUT) model. The research question posed is: “What factors influence the acceptance of the case management system in the Indonesian National Police?” The following sections will review the factors that may influence the use of the case management system in Indonesia. The research approach is then explained. The research results are reported and discussed further. Finally, conclusions will be drawn as a closing.

B. Research Framework and Hypotheses Development

UTAUT Model

The Unified Theory of Acceptance and Use of Technology (UTAUT) model is one of the most widely used models to explain the factors that influence the acceptance and use of information technology in organizational environments. Four main factors that are crucial direct determinants of user acceptance and usage behavior in the UTAUT model are performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) [2].

The UTAUT model has been modified and expanded to explain the acceptance and use of new technology applications in various previous studies with different fields, such as software engineering tools [3], digital payments [4], [5], or virtual assistants [6]. The results show that UTAUT can be a good tool to analyze user acceptance of certain technologies.

However, no model has been specifically designed to evaluate the acceptance of e-government systems with government policies and regulations as one of its main constructs. Therefore, the aim of this research is to study the acceptance and use of e-government systems in Indonesia by expanding UTAUT through the addition of a new construct, namely: government policies and regulations (see Figure 1).

Goverment Policy and Regulations

Government policy is considered a declaration of political activities, plans, and government intentions regarding a particular action, which affects the quality of life of the community [4]. With the increasing development of technology and high levels of uncertainty related to investments in technology development, the government has developed a number of different policies to stimulate technological innovation [7].

The impact of government policies and regulations has been empirically tested in various IT innovation contexts. Previous research shows that government policies and regulations can encourage citizens' attitudes to adopt *e-government* [8], have a significant relationship with cloud computing assimilation [9], promote the sustainability of mobile payment services [10], reduce barriers in the adoption of Industry 4.0 [11], have a positive effect in encouraging *blockchain* adoption [12], influence citizens' decisions to use *bitcoin* payments [4], and affect the use of electronic money services [13]. These policies sometimes have the desired effect, but in many cases, they do not have the expected effect [7].

H1: Government policies and regulations (GPR) have a positive influence on behavioral intention (BI).
H1a: The influence of GPR on BI is moderated by gender.
H1b: The influence of GPR on BI is moderated by age.
H1c: The influence of GPR on BI is moderated by experience.

Performance Expectancy (PE)

Performance expectancy is defined as the level to which someone believes that using the system will help them achieve benefits in their work [2]. Several previous studies have tested that performance expectancy has a significant impact on the intention to use an information system [2], [3], [8], and specifically, it has an influence on the intention to adopt *e-government* [14]–[16].

H2: Performance expectancy (PE) has a positive influence on behavioral intention (BI).
H2a: The influence of PE on BI is moderated by gender.
H2b: The influence of PE on BI is moderated by age.

Effort Expectancy (EE)

Effort expectancy is defined as the level of ease associated with using the system [2]. Several previous studies show that effort expectancy has an impact on the intention to use an information system [2], [4], and specifically, it has an influence on the intention to use *e-government* systems [15], [16], while other studies prove that effort expectancy does not significantly affect the use of *e-government* [14].

H3: Effort expectancy (EE) has a positive influence on behavioral intention (BI).
H3a: The influence of EE on BI is moderated by gender.
H3b: The influence of EE on BI is moderated by age.
H3c: The influence of EE on BI is moderated by experience.

Social Influence (SI)

Social influence is defined as the degree to which someone perceives that important others believe they should use the new system [2]. Several previous studies have tested that social influence has a significant impact on the intention to use a system [2], [16], and specifically, it has an influence on the intention to use *e-*

government systems [15], [17]. The influence of family, friends, and colleagues has some impact on a person's intention to adopt and use socially accepted systems, such as *e-government* [15]. However, social influence can also be considered an insignificant factor affecting user attitudes towards *e-government* services, as this may occur if users have sufficient experience with *e-government* portals so that the influence of social networks has decreased [17].

H4: Social influence (SI) has a positive influence on behavioral intention (BI).
H4a: The influence of SI on BI is moderated by gender.
H4b: The influence of SI on BI is moderated by age.
H4c: The influence of SI on BI is moderated by experience.

Facilitating Conditions (FC)

Facilitating conditions are defined as the degree to which individuals believe that organizational and technical infrastructure exists to support system usage, or ways to achieve a goal by providing the necessary support or resources [2]. In several previous studies, the influence of facilitating conditions has been proven to have a significant relationship with system usage behavior [2], [3], [18], and specifically, it positively affects the use of *e-government* systems [16].

H5: Facilitating conditions (FC) have a positive influence on usage behavior (UB).
H5a: The influence of FC on UB is moderated by age.
H5b: The influence of FC on UB is moderated by experience

Behavioral Intention (BI)

Based on a survey conducted by Bappenas in 2020 on investigators and assistant investigators of Indonesian National Police who are users of the CMS system, only 7.2% of investigators have fully used the CMS application in their case administration, 67.3% still conduct case administration manually, and the remaining 25.5% handle case administration using a combination of manual and system methods.

H6: Behavioral intention (BI) has a positive influence on usage behavior (UB)

C. Research Method

In general, this study uses a mixed-method approach to collect and analyze data. Data collection was conducted by distributing questionnaires to users of the CMS system throughout Indonesia using *"Google Forms"*. The questionnaire items were adapted from previous studies where a numerical scale was used in the form of a Likert scale from 1 to 5, but adjustments were made to the statement formulations to reflect the content of this study.

Simple random sampling was used for sampling. Valid responses received from the questionnaires were analyzed using SmartPLS. The partial least square structural equation modeling (SEM) technique was applied for statistical relationships in this research model.

The research model to be studied is shown in Figure 1. The factors considered in this model are government policies and regulations (GPR), performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), and investigators' intention (BI) to use the CMS system.

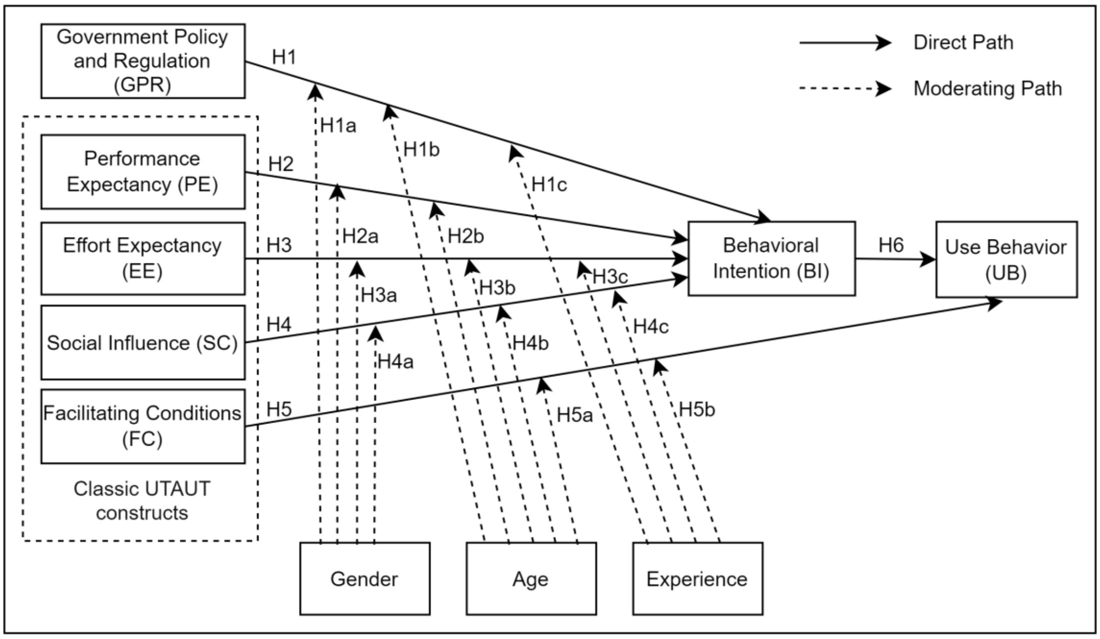

Figure 1. The Proposed Unified Model of CMS Adoptions

D. Result and Discussion

The total number of questionnaires collected in this study was 2003 responses. A total of 499 responses were considered invalid because they provided the same value for all statements, so the data used in this study is 1504 responses. Male respondents comprised 91.22% and female respondents 8.78%. The majority of respondents were in the 35-44 year age group and also the majority had more than 4 years of experience (35.51%). The respondent profile information is presented in Table 1.

To understand the general overview of the observed data, descriptive statistics of the variables can be seen in Table 2. The GPR variable with an average value of 4.4138 indicates that the general perception of users towards the use of the CMS system is very positively influenced by the existence of policies and regulations. The PE variable with an average value of 4.4406 reflects high performance expectancy from users towards the system. The EE variable with an average value of 4.1294 shows that users feel that the effort required to use the CMS system is lower compared to the influence of GPR and PE. The SI variable with an average value of 3.9239 indicates that social influence does not significantly affect users. The FC variable with an average value of 4.3852 indicates that the conditions supporting the use of the CMS system are considered quite good by users.

At the initial stage of analysis, assumptions were tested using the Structural Equation Model (SEM) framework. Testing these assumptions is important to determine whether the data meets the requirements for further analysis using the SEM method. Assumption testing included minimum sample test and normality test. In SEM modeling, the recommended minimum sample size is 100. The data collected from the questionnaires is from 1504 respondents. Therefore, the amount of data in this study meets the requirements for testing with the SEM model.

Table 1. Respondent Profile

	Items	Frequency	Percentage
Gender	Male	1372	91,22%
	Female	132	8,78%
Age	< 18	0	0%
	18-24	118	7,85%
	25-34	480	31,91%
	35-44	684	45,48%
	45-55	202	13,43%
	> 55	20	1,33%
Experiences	< 1 year	210	13,96%
	1-2 years	338	22,47%
	3-4 years	437	29,06%
	> 4 years	519	34,51%

Table 2. Descriptive Analysis

Variable	N	Minimum	Maximum	Mean	Std. Deviation
GPR	1504	1.00	5.00	4.4138	.78386
PE	1504	1.00	5.00	4.4406	.83912
EE	1504	1.00	5.00	4.1294	.88753
SI	1504	1.00	5.00	3.9239	.77452
FC	1504	1.00	5.00	4.3852	.79558
BI	1504	1.00	5.00	4.4096	.79574
UB	1504	1.00	5.00	4.3515	.91113
Valid N (listwise)	1504				

Data is said to have a normal distribution if the univariate (skewness and kurtosis) and multivariate critical ratio values are below 1.96. Based on Table 3, the critical ratio of skewness for each variable has a value below 1.96, but the critical ratio of kurtosis for most indicators has a value greater than 1.96, and the multivariate critical ratio is also greater than 1.96. This indicates that the data is not normally distributed both univariately and multivariately.

Because the normality test results indicate that the data does not have a normal distribution, SEM testing continued using the Partial Least Squares Structural Equation Modeling (PLS-SEM) model. PLS-SEM is a more flexible approach to data distribution assumptions and is suitable for addressing non-normality issues.

In the PLS-SEM analysis, three testing steps must be performed: evaluating the measurement model or outer model, evaluating the structural model or inner model, and evaluating the model fit and goodness.

Measurement Model

The outer model evaluation is conducted to measure whether the indicators used can describe the variables tested. This evaluation can be done with validity and reliability tests. The validity test ensures that the research instrument measures what it is supposed to measure. This test consists of convergent validity and discriminant validity tests. Convergent validity ensures that the indicators used can adequately measure the same construct, while discriminant validity ensures that different constructs do not highly correlate with each other.

To test convergent validity, *factor loading* and *Average Variance Extracted* (AVE) are used. A variable is considered to have good convergent validity if its loading value is greater than or equal to 0.708 and its AVE value is greater than or equal to 0.50.

In this study, not all items have a loading factor value greater than 0.708, as shown in Table 4. Items with a very low *loading factor* (below 0.40) must be removed as they poorly reflect the measured variable [19]. Indicators with a *loading factor* between 0.40 and 0.708 are removed only if they reduce convergent validity above the recommended threshold. Therefore, in this study, the EE3 indicator was retained, but the SI4 and SI5 indicators were removed. After removing these indicators, the Average Variance Extracted (AVE) test was performed, and all AVE values were above the 0.50 threshold. Thus, the data meets the requirements for good convergent validity.

Discriminant validity tests relate to the principle that different constructs should not highly correlate with each other. In this test, the Heterotrait-Monotrait ratio (HTMT) should be less than or equal to 0.90, which can be confirmed through the Fornell-Larcker criterion and cross-loadings, where the square root of the AVE of a variable should be greater for itself than its correlation with other variables.

Table 3. Univariate and Multivariate Normality Test

Variable	min	max	skew	c.r.	kurtosis	c.r.
UB1	1.000	5.000	-1.681	-26.607	2.465	19.513
UB2	1.000	5.000	-1.585	-25.091	2.119	16.772
UB3	1.000	5.000	-1.504	-23.819	1.923	15.219
BI1	1.000	5.000	-1.703	-26.968	2.686	21.262
BI2	1.000	5.000	-1.636	-25.906	2.528	20.016
BI3	1.000	5.000	-1.582	-25.053	2.593	20.527
FC5	1.000	5.000	-1.609	-25.481	2.406	19.046
FC4	1.000	5.000	-1.581	-25.038	2.176	17.226
FC1	1.000	5.000	-1.642	-26.001	2.587	20.479
FC2	1.000	5.000	-1.666	-26.380	2.858	22.626
FC3	1.000	5.000	-1.699	-26.903	2.914	23.067
SI5	1.000	5.000	-.215	-3.405	-1.427	-11.297
SI4	1.000	5.000	-.241	-3.822	-1.367	-10.822
SI1	1.000	5.000	-1.411	-22.343	1.584	12.535
SI2	1.000	5.000	-1.618	-25.623	2.505	19.832
SI3	1.000	5.000	-1.916	-30.341	3.849	30.469
EE1	1.000	5.000	-1.566	-24.791	2.103	16.648
EE2	1.000	5.000	-1.531	-24.246	1.998	15.821
EE3	1.000	5.000	-.745	-11.793	-.850	-6.725
PE5	1.000	5.000	-1.968	-31.166	3.969	31.420
PE4	1.000	5.000	-1.929	-30.534	3.799	30.072
PE1	1.000	5.000	-1.681	-26.621	2.449	19.384
PE2	1.000	5.000	-1.569	-24.848	1.997	15.807
PE3	1.000	5.000	-1.832	-29.008	3.166	25.065
GPR1	1.000	5.000	-1.548	-24.515	2.242	17.748
GPR2	1.000	5.000	-1.670	-26.438	2.603	20.602
GPR3	1.000	5.000	-1.735	-27.465	3.025	23.947
Multivariate					1361.087	666.936

Table 4. Convergent Validity and Reliability Test

Construct	Item	Factor Loading	AVE	Composite Reliability (CR)	Cronbach's Alpha

	GPR1	0.898			
GPR	GPR2	0.838	0.780	0.914	0.860
	GPR3	0.912			
	PE1	0.916			
	PE2	0.893			
PE	PE3	0.928	0.851	0.966	0.956
	PE4	0.939			
	PE5	0.937			
	EE1	0.948			
EE	EE2	0.941	0.666	0.846	0.727
	EE3	0.459			
	SI1	0.843			
	SI2	0.900			
SI	SI3	0.869	0.772	0.910	0.852
	SI4	0.322			
	SI5	0.156			
	FC1	0.813			
	FC2	0.919			
FC	FC3	0.909	0.760	0.941	0.921
	FC4	0.847			
	FC5	0.867			
	BI1	0.875			
BI	BI2	0.918	0.797	0.922	0.873
	BI3	0.885			
	UB1	0.927			
UB	UB2	0.960	0.894	0.962	0.941
	UB3	0.949			

The initial HTMT discriminant validity test results did not meet the requirements (see Table 5), with some indicators having an HTMT value greater than 0.90. Therefore, indicators causing high inter-variable correlations were removed, namely GPR3, EE3, FC1, FC5, BI3, UB2, and UB3. After removing these indicators, retesting showed that the HTMT discriminant validity evaluation met the requirements (see Table 6). Discriminant validity evaluation results were also confirmed with the Fornell-Larcker criterion and cross-loading tests, where each variable had a greater square root of AVE for itself than for its correlation with other variables (see Tables 7 and 8). Thus, the data meets the requirements for good discriminant validity.

Reliability refers to the consistency of the measurement of a concept, ensuring that the indicators used are related to each other. Reliability can be tested by measuring Composite Reliability (CR) and Cronbach's Alpha. To meet good reliability criteria, both the Composite Reliability (CR) and Cronbach's Alpha values must be greater than or equal to 0.70, indicating that the indicators within the construct consistently measure the same concept.

Based on the test results shown in Table 4, all variables have Composite Reliability (CR) and Cronbach's Alpha values greater than 0.70, indicating that all indicators used in this study can consistently measure their respective variables and have good reliability. Thus, the measurements used can be considered accurate and trustworthy.

Table 5. HTMT Ratio Before

Construct	GPR	PE	EE	SI	FC	BI	UB
GPR							
PE	0.830						

EE	0.846	0.937					
SI	0.923	0.893	0.910				
FC	0.933	0.860	0.895	0.925			
BI	0.936	0.897	0.906	0.928	0.951		
UB	0.862	0.880	0.917	0.874	0.924	0.928	

Table 6. HTMT Ratio After

Construct	GPR	PE	EE	SI	FC	BI	UB
GPR							
PE	0.783						
EE	0.766	0.888					
SI	0.885	0.893	0.873				
FC	0.868	0.832	0.803	0.899			
BI	0.850	0.893	0.830	0.898	0.881		
UB	0.749	0.790	0.748	0.783	0.820	0.819	

Table 7. Fornell-Larcker criterion

Construct	GPR	PE	EE	SI	FC	BI	UB
GPR	0.906						
PE	0.688	0.923					
EE	0.657	0.832	0.960				
SI	0.729	0.807	0.770	0.879			
FC	0.740	0.774	0.729	0.786	0.914		
BI	0.695	0.801	0.727	0.761	0.767	0.926	
UB	0.672	0.772	0.716	0.721	0.778	0.750	1.000

Table 8. Cross Loading

Construct	GPR	PE	EE	SI	FC	BI	UB
GPR1	0.926	0.701	0.660	0.704	0.757	0.688	0.691
GPR2	0.886	0.531	0.518	0.609	0.568	0.562	0.512
PE1	0.609	0.917	0.755	0.711	0.693	0.719	0.718
PE2	0.581	0.893	0.720	0.710	0.675	0.691	0.666
PE3	0.629	0.929	0.764	0.742	0.722	0.764	0.724
PE4	0.680	0.938	0.802	0.774	0.747	0.754	0.730
PE5	0.671	0.936	0.794	0.781	0.732	0.763	0.724
EE1	0.648	0.828	0.962	0.766	0.721	0.719	0.708
EE2	0.611	0.768	0.957	0.710	0.678	0.676	0.666
SI1	0.592	0.679	0.697	0.849	0.718	0.630	0.658
SI2	0.672	0.732	0.671	0.908	0.679	0.704	0.643
SI3	0.654	0.714	0.665	0.878	0.679	0.669	0.602
FC2	0.708	0.753	0.699	0.754	0.933	0.739	0.724
FC3	0.709	0.746	0.671	0.715	0.935	0.728	0.727
FC4	0.609	0.619	0.628	0.685	0.872	0.632	0.680
BI1	0.623	0.686	0.631	0.648	0.664	0.916	0.649
BI2	0.661	0.791	0.712	0.755	0.751	0.935	0.735
UB1	0.672	0.772	0.716	0.721	0.778	0.750	1.000

Structural Model

Before testing the structural model, it is important to check for multicollinearity among the variables using the Inner Variance Inflated Factor (VIF). Collinearity refers to the correlation between two independent variables, while multicollinearity refers to the correlation among three or more independent variables [20]. Multicollinearity can reduce the predictive power of each independent variable. A VIF value above 5 indicates the possibility of collinearity problems among the predictor constructs [21]. The test results show that there is no multicollinearity among the variables tested (see Table 9).

Table 9. Inner VIF

Construct	BI	UB
GPR	2.294	
PE	4.267	
EE	3.609	
SI	3.636	
FC		2.429
BI		2.429
UB		

To test the relationships between variables, hypothesis testing is used. The path coefficient is a number that indicates the strength and direction of the relationship between variables in the structural model, while the p-value is the probability of rejecting the null hypothesis stating that there is no relationship between the variables. A significant path coefficient (path coefficient greater than 1.96 and p-value less than 0.05) indicates a significant relationship. The test results show that GPR, PE, and SI have a significant effect on BI, while EE does not. Then FC and BI have a direct and significant effect on UB (see Table 10).

Table 10. Hypotesis Test

Hypothesis	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Support
H1: GPR -> BI	0.190	0.191	0.034	5.662	0.000	Yes
H2: PE -> BI	0.434	0.431	0.054	8.082	0.000	Yes
H3: EE -> BI	0.078	0.079	0.045	1.723	0.085	No
H4: SI -> BI	0.212	0.214	0.050	4.235	0.000	Yes
H5: FC -> UB	0.492	0.491	0.053	9.339	0.000	Yes
H6: BI -> UB	0.373	0.374	0.054	6.942	0.000	Yes

To test the moderating effects of age, gender, and experience, the significance of path coefficients based on age, gender, and experience categories was tested. Based on gender, shown in Table 11, the effect of GPR on BI is stronger in males, the effect of PE on BI is significant in males but not significant in females, the effect of EE on BI is not significant in males but significant in females, and the effect of SI on BI is stronger in males.

Based on the age groups shown in Table 12, age does not moderate the relationship between GPR, PE, and EE with BI but moderates the influence of SI on BI and the influence of FC on UB. The influence of SI on BI tends to increase with older age groups. The influence of FC on UB is significant in older age groups and not significant in younger age groups. Experience does not moderate the relationship between GPR, EE, and SI with BI, but it does moderate the influence of FC on UB, where the influence increases with more experience, as shown in Table 13.

Table 11. The Impact of Gender on CMS

Hypothesis	Male	Female	Support
H1: GPR -> BI	0.000	0.046	Yes
H2: PE -> BI	0.000	0.909	Yes
H3: EE -> BI	0.112	0.047	Yes
H4: SI -> BI	0.000	0.022	Yes
H5: FC -> UB	0.000	0.121	Yes
H6: BI -> UB	0.000	0.004	Yes

Table 12. The impact of age on CMS

Hypothesis	<24	25-34	35-44	>45	Support
H1: GPR -> BI	0.003	0.001	0.001	0.072	No
H2: PE -> BI	0.078	0.000	0.000	0.042	No
H3: EE -> BI	0.216	0.368	0.452	0.384	No
H4: SI -> BI	0.775	0.209	0.001	0.000	Yes
H5: FC -> UB	0.981	0.000	0.000	0.000	Yes
H6: BI -> UB	0.000	0.000	0.000	0.466	Yes

Table 13. The impact of experiences on CMS

Hypothesis	<1	1-2	3-4	>4	Support
H1: GPR -> BI	0.056	0.000	0.002	0.012	No
H2: PE -> BI	0.107	0.000	0.000	0.000	Yes
H3: EE -> BI	0.166	0.007	0.332	0.863	No
H4: SI -> BI	0.017	0.063	0.050	0.009	No
H5: FC -> UB	0.121	0.001	0.000	0.000	Yes
H6: BI -> UB	0.000	0.000	0.000	0.011	Yes

To interpret the significance and strength of the relationships between variables in the structural model and to provide an overview of the accuracy of the path coefficient estimates, a 95% confidence interval evaluation was conducted, as shown in Table 14. To determine whether a variable directly influences another variable or indirectly influences through another intermediary variable, a mediation test was conducted, as shown in Table 15.

Table 14. Interval Confidence 95%

Construct	Original sample (O)	Sample mean (M)	2.5%	97.5%
GPR -> BI	0.190	0.191	0.126	0.258
GPR -> UB	0.071	0.072	0.041	0.110
PE -> BI	0.434	0.431	0.322	0.533
PE -> UB	0.162	0.162	0.101	0.233
EE -> BI	0.078	0.079	-0.007	0.170
EE -> UB	0.029	0.030	-0.003	0.066
SI -> BI	0.212	0.214	0.118	0.314
SI -> UB	0.079	0.079	0.044	0.122
FC -> UB	0.492	0.491	0.386	0.592
BI -> UB	0.373	0.374	0.272	0.483

Table 15. Indirect Effects

Construct	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values

GPR -> BI -> UB	0.071	0.072	0.017	4.077	0.000
PE -> BI -> UB	0.162	0.162	0.034	4.745	0.000
EE -> BI -> UB	0.029	0.030	0.018	1.651	0.099
SI -> BI -> UB	0.079	0.079	0.020	4.034	0.000

Model Goodness and Fit

To determine if the model used in the research has a good *goodness of fit* in predicting relationships between variables, an evaluation of the goodness and fit of the model was conducted. Several methods to test this include looking at r-*square*, q-*square*, f-*square*, SRMR, PLS*Predict*, and *linearity* values.

The predictive capability of the model is considered low if the r-*square* value is below 0.19, moderate if it reaches 0.33, and high if it reaches 0.6 [22]. Additionally, a Q^2 *predict* value greater than zero indicates good predictive capability of the model. If the q-*square* value is less than or equal to 0.25, the predictive capability is considered low, if greater than 0.25 and less than or equal to 0.50, it is considered moderate, and if above 0.50, it is considered high. The r-*square* and q-*square* testing results indicate that the model has good predictive capability (see Table 16).

The F Square testing was conducted to see how much influence an independent variable has on a dependent variable in the structural model. An f-*square* value less than or equal to 0.02 indicates weak variable influence, a value of 0.15 indicates moderate variable influence, and a value of 0.35 indicates strong variable influence. The f-*square* testing results for this research are shown in Table 17.

Standardized Root Mean Square Residual (SRMR) is a measure of model fit indicating how well the theoretical model matches the empirical data. Lower SRMR values indicate better model fit. A good SRMR value ranges from 0 to 0.05, but values above 0.05 up to 0.10 are still acceptable [23]. The SRMR testing results for the model are shown in Table 18.

To effectively assess the out-of-sample predictive power of a model, PLSPredict is used [24], with *Root Mean Squared Error* (RMSE) representing the average squared prediction error and *Mean Absolute Error* (MAE) representing the average absolute error. In this study, PLSPredict was used to compare the performance of the PLS-SEM model with the linear regression model (LM). The results showed that the PLS-SEM model had fairly good predictive capability with a reasonably high Q^2 *predict* value. However, the linear regression model (LM) performed slightly better (see Table 19).

To determine whether the assumption of linearity between variables is met, a linearity test was conducted. Significant quadratic coefficients between variables (-*value* less than or equal to 0.05) indicate non-linear relationships. The results of the linearity test showed that there were no non-linear relationships, confirming that the linearity assumption of the model is met (see Table 20).

Table 16. R Square and Q Square

Construct	R^2	Q^2
BI	0.698	0.692
UB	0.662	0.667

Table 17. F Square

Construct	BI	UB
GPR	0.052	

PE	0.146	
EE	0.006	
SI	0.041	
BI		0.170
FC		0.295
UB		

Table 18. SRMR

Construct	Saturated model	Estimated model
SRMR	0.048	0.052
d_ULS	0.391	0.471
d_G	0.363	0.390
Chi-square	3408.521	3575.463
NFI	0.880	0.874

Table 19. PLS Predict

Construct	Q^2predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
BI1	0.514	0.662	0.331	0.653	0.330
BI2	0.666	0.519	0.298	0.511	0.270
UB1	0.667	0.545	0.284	0.540	0.269

Table 20. Linearity

Construct	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
QE (GPR) -> BI	0.044	0.045	0.024	1.831	0.067
QE (PE) -> BI	-0.026	-0.027	0.032	0.821	0.412
QE (EE) -> BI	0.008	0.008	0.023	0.368	0.713
QE (SI) -> BI	-0.009	-0.010	0.029	0.305	0.760
QE (BI) -> UB	-0.064	-0.064	0.035	1.849	0.064
QE (FC) -> UB	0.025	0.024	0.034	0.717	0.473
QE (GPR) -> BI	0.044	0.045	0.024	1.831	0.067
QE (PE) -> BI	-0.026	-0.027	0.032	0.821	0.412

E. Conclusion

The influence of GPR on BI is supported by several previous studies [4], [8]–[13]. The results of Mensah et al. (2022) indicate that government policies and regulations can drive citizens' attitudes towards adopting *e-government*, where government policies play a unique role in the development and implementation of *e-government* services and the broader dissemination of these services.

The significant influence of PE on BI is also supported in many other studies [2], [14]–[16]. In the context of this study, it can be understood how performance expectations play an important role in the use of the CMS system. A survey conducted by Bappenas in 2020 among users of the CMS system showed that 79.1% of investigators stated that the case handling system is part of the work unit's performance evaluation.

The non-significant influence of EE on BI was also found in several previous studies [3], [14], [25]. The rejection of the hypothesis regarding the relationship between effort expectancy and intention to use the system in this study can be seen as a common response among investigators to the CMS system, where the expectation of the effort required to use the CMS system has not yet been seen as a factor driving users to use the system. In other words, investigators have not yet felt that the simplicity of business processes, the simplicity of interfaces, and the overall ease of using the CMS system are capable of encouraging them to use the system, as reflected in indicators EE1, EE2, and EE3. This is also evident from some findings obtained from the responses to the collected questionnaires, where some investigators indicated that they still face challenges in using the CMS system, such as limitations on the number of documents that can be created and document formats not aligning with the latest Perkaba Mindik. This indicates that many investigators still perceive challenges in using the CMS system.

In this study, social factors were found to be one of the significant factors influencing the intention to use the CMS system, where the support of the Indonesian National Police institution in providing training, discussion forums, technical support, direct supervision by superiors in using the CMS system, and the role of the satker admin in maintaining the quality of documents play an important role in encouraging the use of the CMS system. These results are supported by previous research conducted by [26], but differ from the findings of [3], [17], [25]. In the study by [17] on the factors influencing user perceptions and acceptance of *e-government* services, it was found that the influence of social networks had diminished as users had gathered sufficient experience with the electronic portal.

In this study, facilitating conditions were proven to have a significant direct influence on the behavior of using the system. These results are supported by previous studies that found that facilitating conditions have a positive impact on the use of *e-government* systems [16]. In a survey conducted by Bappenas in 2020 among users of the CMS system, 62.5% of respondents answered that there were available *Personal Computers* (PCs); 16.4% answered that there were no PCs available for conducting investigation administration through the CMS application; and another 16.4% answered that PCs were available but had to be shared. Additionally, 65.2% of CMS system users stated that they had received technical guidance between 2016-2019, and 55% had communicated with the relevant authorities if there were issues. This indicates that the availability of user training, software or hardware, and technical support are factors that encourage investigators to use the CMS system.

F. Acknowledgment

This study shows that government policies and regulations have a significant influence on the use of systems, especially electronic government systems in government agencies such as the CMS system. These findings can serve as a basis for further research to explore how policies and regulations can be optimized to enhance the adoption and use of technology in the public sector. Additionally, collaboration between academics and government agencies can help develop more effective and evidence-based implementation strategies. For future research, qualitative analysis of research results should also be considered to validate the findings from quantitative tests, which due to time constraints could not be conducted in this study and represent a limitation of this research.

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