Government Regulation and the Adoption of E-Government Services: User Satisfaction as a Mediator in an Extended UTAUT Model

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ABSTRACT:

This study examines the factors influencing the adoption of digital public services in Riau Province, Indonesia. A quantitative study was conducted using a Google Forms questionnaire, which yielded 272 valid responses. The research model, an extended UTAUT framework, integrated government regulation (GR) with key antecedents: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). The study investigated user satisfaction (US) and behavioral intention (BI) as mediators. Using PLS-SEM, the findings showed that all 16 hypotheses were significantly supported ($P < 0.05$). All antecedents positively influenced US and BI. Notably, GR had the strongest direct influence on BI ($\beta=0.481$) and the most powerful indirect effect on user behavior (UB) through BI. Both US and BI were confirmed as crucial mediators. In conclusion, this study affirms a robust model where behavioral intention and user satisfaction are key to driving the adoption of public service applications.

Keywords: e- Government, Technology Adoption, UTAUT, User Behavior, SEM PLS

1. Introduction

Government agencies worldwide are increasingly adopting technological innovations in the era of digital transformation (Ibrahim et al., 2023) to deliver services that are more effective (Samsor, 2021), transparent (Islah, 2018), and citizen-oriented (Carter & Bélanger, 2005). E-public services have become a foundational component of contemporary governance, enabling the delivery of administrative, legal, and civic functions through digital platforms (Latupeirissa et al., 2024). As digital governance evolves, both internal and external factors play a crucial role in shaping the success and adoption of e-public services (Wallang, 2018), including the regulatory environment.

In countries experiencing rapid digital advancement, such as Indonesia, coherent and supportive governmental regulations act as key enablers that foster not only digital innovation (Chen et al., 2023) but also strengthen public trust (Minardi, 2020) and increase user adoption (Garnett, 2020). Indonesia's national digital transformation framework, known as the Electronic-Based Government System (SPBE),

has become a central driver in expanding e-public service implementation across the nation (Astawa, 2023). Over the past five years, numerous policies and presidential directives have been introduced to enhance interoperability, standardize service quality, and reinforce data security within ministries and local governments through deeper system integration (Hariguna, 2021).

Aligned with these reforms, the Ministry of Administrative and Bureaucratic Reform (PAN-RB) reports consistent improvements in the SPBE Index across various service domains—such as civil registration, taxation, social assistance, and licensing—reflecting Indonesia's ongoing progress toward more integrated and citizen-responsive digital governance (Astawa, 2023).

Despite ongoing policy reforms, actual public adoption of digital services varies considerably across sectors. Many citizens continue to depend on conventional, in-person services even when digital alternatives are readily available (Maisha & Shetu, 2023). This persistent reliance raises critical questions about the underlying determinants of public acceptance of e-services, suggesting that availability alone is insufficient. Among the various factors shaping user behavior, satisfaction has emerged as a particularly influential construct (Huda & Amin, 2023; Park, 2019; Susanti, 2022). Individuals are more inclined to continue using e-public services when these platforms are perceived as easy to navigate, reliable, responsive, and beneficial. This underscores the importance of examining whether user satisfaction mediates the relationship between regulatory support and actual usage.

In developing its conceptual foundation, this study incorporates government regulation as an external factor. The Unified Theory of Acceptance and Use of Technology (UTAUT), originally proposed by Venkatesh et al., (2003), has been widely adopted across numerous domains—including public-sector innovation—to explain technology acceptance behavior. Building on this framework, the present study extends the model by integrating user satisfaction as a mediating variable, thereby offering deeper insights into how public perceptions and experiential evaluations shape the adoption of government digital services.

Practically, the findings delineate operational levers for policymakers and public managers to enhance e-service uptake. Specifically, the analysis indicates that Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC), in conjunction with Government Regulation (GR), exert their influence on Actual Use (AU) indirectly via Behavioral Intention (BI) and User Satisfaction (US) as mediating mechanisms. As public expectations evolve in parallel with technological advancements, government institutions must continually assess user satisfaction and address service gaps that hinder sustained utilization (McQuiston & Manoharan, 2021). Thus, the effectiveness of e-public services is determined not only by regulatory frameworks but also by the extent to which these policies translate into meaningful and positive citizen experiences (Duisenkul et al., 2023).

Grounded in contemporary digital governance and guided by the Unified Theory of Acceptance and Use of Technology (UTAUT), this study explores the nexus between government regulation, user satisfaction, and the adoption of e-public services. Based on empirical data collected from e-service users in Riau Province, Indonesia, the inquiry is structured around the following research questions:

RQ1: To what extent do the UTAUT constructs and government regulations influence citizens' acceptance of e-public services??

RQ2: How do the UTAUT constructs and government regulations shape user satisfaction with e-public services?

RQ3: To what extent does behavioral intention mediate the relationship between the UTAUT constructs, government regulations, and users' engagement with e-public services?

RQ4: To what extent does user satisfaction mediate the relationship between the UTAUT constructs, government regulations, and users' behavioral outcomes in the context of e-public services?

RQ5: Among the UTAUT constructs, government regulations, behavioral intention, and user satisfaction, which factors most strongly predict the actual use of e-public services?

2. The Comprehensive Theoretical Basis

2.1. Theoretical Basis

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al., (2003) was formulated to integrate and consolidate various existing models of technology adoption. The model draws on several foundational theories, including the Diffusion of Innovation (DOI) theory (Rogers, 1962), the Technology Acceptance Model (TAM) (Davis, 1989), the Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 1969),), the Theory of Planned Behavior (Ajzen, I., & Fishbein, 1980), the Motivation Model (Davis et al., 1989), and Social Cognitive Theory (Bandura, 1991). As originally formulated, the UTAUT framework delineates four key determinants: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC), that influence users' behavioral intention and actual technology use.

UTAUT has emerged as a leading framework in information systems research owing to its substantial predictive validity, explaining a large share of variance in user behavior, often approaching 70 percent in intention-to-use models. (Venkatesh et al., 2003). The model has been successfully applied across diverse domains, including mobile commerce (Al-Saedi, 2019; Daniali, 2022; Mohammed A.Sabri Alrawi et al., 2020; Zhang et al., 2019), e-learning systems (Abbad, 2021; Jameel, 2022; Sholikah & Dwi Harsono, 2021), mobile banking (Jadil, 2021; Kwateng et al., 2019; Mensah & Khan, 2024; Raza, 2019), and digital payment services (Haryanto et al., 2023; Manrai, 2021; Ponsree et al., 2021).

Within the UTAUT framework, performance expectancy, effort expectancy, and social influence have consistently been shown to exert a direct influence on users' intentions to adopt technology (Tang, 2021). Facilitating conditions—defined as the availability of requisite resources, infrastructure, and technical support—exhibit mixed empirical effects across studies. While several investigations report significant associations with perceived ease of use and behavioral intention, findings are context-dependent and not uniformly consistent (Sobti, 2019).

Among the UTAUT constructs, performance expectancy consistently emerges as the most influential predictor, reflecting users' beliefs that system use will improve task performance. This salience is especially pertinent in the context of e-public service adoption, where efficiency and service quality are paramount.

2.2. Research Model and Hypotheses

The study broadens the UTAUT framework by treating government regulation (GR) as an external antecedent and by conceptualizing user satisfaction (US) as a mediator. Its principal contribution is to elucidate how GR exerts indirect influence on the use of e-public services through the mediating channels of US and behavioral intention (BI).

The study's novelty is further strengthened by positioning US as a mediator between performance expectancy (PE) and effort expectancy (EE) and downstream adoption outcomes, thereby integrating regulatory and user-centric levers within a single explanatory model. This extension is particularly relevant for the development of digital public services, where regulatory design plays a pivotal role in shaping user responses and fostering service uptake.

In the proposed specification, performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), and government

regulation (GR) are treated as independent variables. Each is hypothesized to influence behavioral intention (BI) and user satisfaction (US), with these proximal outcomes jointly informing downstream usage behavior (UB) of e-public services. User satisfaction is conceptualized as an affective evaluation arising from users' experiences with the service, whereas behavioral intention reflects users' willingness and readiness to engage with the service in the foreseeable future. The conceptual framework of this study is presented in Figure 1.

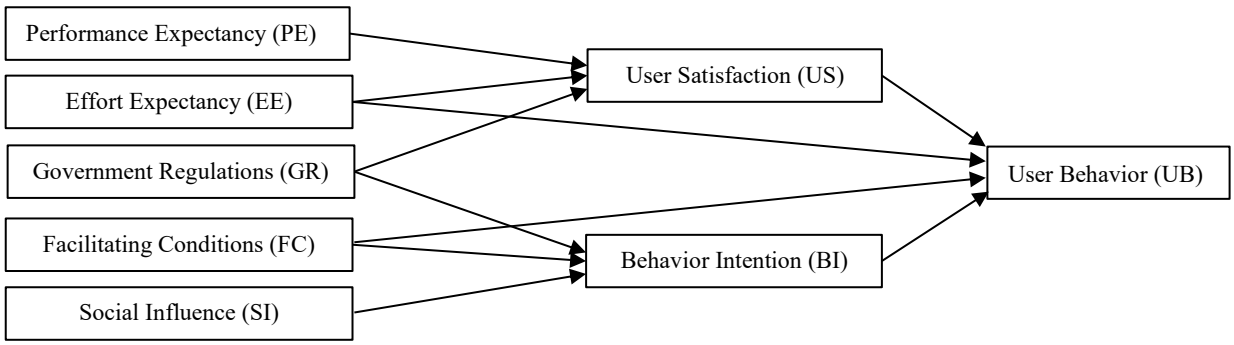

Figure 1. Conceptual framework of the study

Based on the proposed conceptual framework, the following hypotheses are formulated:

H1: Performance Expectancy (PE) positively influences User Satisfaction (US).

H2: Effort Expectancy (EE) positively influences User Satisfaction (US).

H3: Government Regulation (GR) positively influences User Satisfaction (US).

H4: Government Regulation (GR) positively influences Behavioral Intention (BI).

H5: Facilitating Conditions (FC) positively influence Behavioral Intention (BI).

H6: Social Influence (SI) positively influences Behavioral Intention (BI).

H7: Effort Expectancy (EE) positively influences Usage Behavior (UB).

H8: Facilitating Conditions (FC) positively influence Usage Behavior (UB).

H9: User Satisfaction (US) positively influences Usage Behavior (UB).

H10: Behavioral Intention (BI) positively influences Usage Behavior (UB).

H11: User Satisfaction (US) mediates the relationship between Performance Expectancy (PE) and Usage Behavior (UB).

H12: User Satisfaction (US) mediates the relationship between Effort Expectancy (EE) and Usage Behavior (UB).

H13: User Satisfaction (US) mediates the relationship between Government Regulation (GR) and Usage Behavior (UB).

H14: Behavioral Intention (BI) mediates the relationship between Government Regulation (GR) and Usage Behavior (UB).

H15: Behavioral Intention (BI) mediates the relationship between Facilitating Conditions (FC) and Usage Behavior (UB).

H16: Behavioral Intention (BI) mediates the relationship between Social Influence (SI) and Usage Behavior (UB).

3. Method

3.1. Research Design

Research design denotes the systematic, logical blueprint that structures a study to achieve its objectives efficiently and validly. This study employs a quantitative approach, commencing with the articulation of research questions and the derivation of testable hypotheses from a comprehensive review of the relevant literature (Antwi & Hamza, 2015;

Apuke, 2017; Mohajan, 2020; Takona, 2024). Guided by the UTAUT framework, the study formulates a theoretical model that integrates government regulation (GR) as an exogenous predictor and user satisfaction (US) as an intervening mechanism to account for the adoption of e-public services. The hypothesized relationships were examined using numerically coded responses from a structured questionnaire and subjected to partial least squares structural equation modeling (PLS-SEM) in SmartPLS (version 4.1.1.2).

3.2. Data Collection and Measurement

A structured questionnaire was developed to evaluate the research hypotheses (Mohajan, 2020; Taherdoost, 2021). The instrument consists of three sections: (1) an introductory statement outlining the purpose and significance of the study, (2) demographic information about the respondents; and (3) the main section containing measurement items derived from the proposed model.

All measurement items were adapted from previously validated studies and contextualized for the e-government environment. Each item was designed to capture perceptions associated with the constructs under investigation. A seven-point Likert scale was used to measure respondents' level of agreement, ranging from 1 ("strongly disagree") to 7 ("strongly agree") (Arnold et al., 1967; Joshi & Pal, 2015; Yamashita, 2022).

3.3. Sampling Technique and Size

This study targeted users of digital public services across several cities in Riau Province, Indonesia, employing a non-probability sampling technique, specifically convenience sampling (Makwana et al., 2023). The questionnaire was distributed through government service networks and online platforms. Of the 296 questionnaires collected, 272 were deemed valid and used for analysis, representing 84% of the total responses. Twenty-four responses were excluded for several reasons, including unrealistically rapid completion time, duplicate submissions, and respondents who did not meet the population criteria (i.e., not residents of the targeted area).

The final sample size is deemed adequate for PLS-SEM analyses, especially when corroborated by robust measurement properties, including acceptable indicator reliability, internal consistency, convergent validity, and discriminant validity, prior to testing the structural paths (Cheah et al., 2021; Gimeno-Arias & Santos-Jaén, 2023; Hair, Sarstedt, et al., 2019; Memon et al., 2021).

3.4. Data Analysis Method

The collected data were analyzed using SmartPLS (version 4.1.1.2), software designed for Partial Least Squares Structural Equation Modeling (PLS-SEM) (Hair, Sarstedt, et al., 2019; Khan et al., 2019; Richter et al., 2022; Sarstedt et al., 2020). The selection of this analytical tool is justified by two primary considerations: (1) its suitability for evaluating complex models involving mediating variables such as user satisfaction, and (2) its robustness when applied to small and medium-sized samples. Analyses were conducted in two phases, beginning with measurement model evaluation—confirming reliability and validity criteria—followed by structural model estimation to test the proposed relationships. Accounting for the mediating pathway of user satisfaction (US), the evidence reveals both direct and indirect influences of government regulation (GR) on citizens' adoption of e-public services.

This analytical approach underscores the importance of user satisfaction in strengthening e-government implementation and contributes empirical evidence on how regulatory frameworks shape public sector technology adoption,

4. Results And Discussion

To evaluate the proposed hypotheses, data analysis was conducted after the conceptual research model was established and respondent data had been successfully collected. This study employs the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique,

implemented using SmartPLS 4 (version 4.1.1.2).

The PLS-SEM procedure requires a systematic two-stage assessment, which is critical to ensure that the conclusions drawn from the hypothesis testing are based on a robust structural and measurement model. These two stages consist of the following:

4.1. Assessment of the Measurement Model (Outer Model)

This initial phase can be likened to constructing the foundation of a building. Before examining the structural relationships between variables, it is essential to ensure that the measurement foundation is strong and stable. The assessment of the outer (measurement) model is undertaken to evaluate indicator-level and construct-level quality in terms of validity and reliability for all latent variables (Khan et al., 2019). Conducting this evaluation ensures that the instrumentation is accurate (valid) and internally consistent (reliable) before proceeding to estimate the structural paths. If the measurement model is found to be invalid or unreliable, the results of subsequent hypothesis testing cannot be considered trustworthy.

4.1.1. Convergent validity and Construct reliability Test Result

To ensure adequacy prior to structural testing, the measurement model is evaluated for internal consistency reliability, convergent validity, and discriminant validity. Convergent validity and construct reliability are the principal checks: loadings should generally be greater than 0.70, AVE should be at least 0.50, and reliability indices—Cronbach's alpha, rho_A, and composite reliability (CR)—are expected to exceed 0.70, indicating satisfactory indicator quality and construct consistency.(Hair et al., 2020).

As shown in Table 1, high factor loadings, AVE values greater than 0.50, and strong reliability indicators confirm the constructs' validity and internal consistency (Hair, Risher, et al., 2019).

Table 1 Convergent validity and Construct reliability Test Result

Construct	Item	Convergent validity			Construct reliability			
		Loading factors	AVE	Remark	Cronbach's alpha	rho_A	Composite reliability	Remark
PE	PE1	0,821	0,726	Valid	0,874	0,874	0,914	Reliable
	PE2	0,890						
	PE3	0,855						
	PE4	0,840						
EE	EE1	0,869	0,775	Valid	0,903	0,903	0,932	Reliable
	EE2	0,889						
	EE3	0,882						
	EE4	0,880						
GR	GR1	0,851	0,749	Valid	0,888	0,889	0,923	Reliable
	GR2	0,872						
	GR3	0,862						
	GR4	0,876						
FC	FC1	0,845	0,698	Valid	0,856	0,856	0,902	Reliable
	FC2	0,826						
	FC3	0,836						
	FC4	0,835						
SI	SI1	0,853	0,732	Valid	0,878	0,878	0,916	Reliable
	SI2	0,861						

	SI3	0,866						
	SI4	0,844						
US	US1	0,886	0,764	Valid	0,897	0,897	0,928	Reliable
	US2	0,875						
	US3	0,864						
	US4	0,871						
BI	BI1	0,872	0,777	Valid	0,904	0,904	0,933	Reliable
	BI2	0,882						
	BI3	0,884						
	BI4	0,888						
UB	UB1	0,833	0,673	Valid	0,838	0,840	0,892	Reliable
	UB2	0,816						
	UB3	0,784						
	UB4	0,848						

Convergent validity testing is employed to evaluate how effectively each indicator represents its corresponding latent construct. The results indicate that all criteria for convergent validity are fully met. Each indicator demonstrates a factor loading substantially above the recommended threshold of 0.70. Moreover, all constructs exhibit Average Variance Extracted (AVE) values that exceed the minimum requirement of 0.50, with the lowest AVE recorded at 0.673. These results confirm that all indicators used in this study are valid and accurately capture the constructs they are intended to measure.

Construct reliability is assessed concurrently to ensure the internal consistency of the measurement instrument. The results show that all constructs demonstrate exceptionally strong reliability. Composite reliability values range from 0.892 to 0.933, surpassing the widely accepted minimum threshold of 0.70. Similarly, Cronbach's alpha and rho_A values also exceed the recommended cutoff of 0.70, indicating highly satisfactory reliability levels. Taken together, these findings confirm the consistency and dependability of each set of indicators in measuring their respective constructs within the proposed model.

4.1.2. Discriminant Validity

After confirming convergent validity, the next step in the outer model assessment is evaluating discriminant validity, which ensures that each indicator truly measures the construct it is intended to represent. This assessment verifies that every construct in the research model is empirically distinct and does not exhibit excessive conceptual overlap with other constructs. A construct is considered to possess adequate discriminant validity when it captures a unique concept that is not reflected by any other construct within the model.

Discriminant validity is frequently examined using the Fornell–Larcker criterion, which requires that, for each latent variable, the square root of its AVE be greater than its correlations with any other latent variable. Consistent with standard reporting conventions, the results table places √AVE values on the bolded diagonal and lists inter-construct correlation coefficients below the diagonal to facilitate inspection. To satisfy the Fornell–Larcker requirement, every diagonal value must be greater than all values in the corresponding column beneath it (Shmueli et al., 2019). Table 2 presents the complete results of the discriminant validity assessment using the Fornell–Larcker criterion:

Table 2. The Fornell-Larcker Criterion Test Result

	BI	EE	FC	GR	PE	SI	UB	US
BI	**0,881**							
EE	0,876	**0,880**						
FC	0,796	0,838	**0,835**					
GR	0,859	0,852	0,808	**0,865**				
PE	0,839	0,858	0,821	0,823	**0,852**			
SI	0,829	0,825	0,817	0,819	0,833	**0,856**		
UB	0,829	0,852	0,800	0,822	0,806	0,789	**0,820**	
US	0,850	0,842	0,812	0,840	0,835	0,850	0,815	**0,874**

Discriminant validity was evaluated using the Fornell–Larcker criterion, as summarized in Table 2. By this standard, the square root of each construct's AVE (displayed on the bolded diagonal) must exceed its bivariate correlations with all other constructs (reported below the diagonal). The results confirm compliance, with diagonal coefficients—from 0.881 for BI to 0.874 for US—consistently surpassing the corresponding inter-construct correlations, thereby substantiating discriminant validity.

In conjunction with satisfactory Cronbach's alpha, composite reliability, and AVE statistics, the measurement model demonstrates acceptable reliability and validity, permitting advancement to structural model assessment.

4.2. Assessment of the Structural Model (Inner Model)

Following confirmation of reliability and validity in the measurement (outer) model, the structural (inner) model is assessed to appraise the causal architecture among latent constructs and to test the study's hypotheses. This phase reorients the analysis from verifying indicator–construct alignment to estimating the significance and magnitude of the structural paths, thereby evaluating the model's explanatory and predictive performance.

Several key criteria are assessed to determine the robustness of the structural model, including: a) Path Coefficients (β): Used to evaluate the direction and magnitude of relationships between constructs, forming the basis for hypothesis acceptance or rejection; b) Coefficient of Determination (R^2): Indicates the extent to which independent variables explain the variance in each dependent variable; c) Predictive Relevance (Q^2): Assesses the model's predictive capability for the endogenous constructs; d) Effect Size (f^2): Measures the substantive impact of an independent variable on a dependent variable (Chin et al., 2020; Dennis Cook & Forzani, 2023; Hair & Sarstedt, 2019; Sarstedt & Liu, 2024).

A comprehensive discussion of the results for each of these evaluation criteria is presented in the following section to provide a clear and systematic interpretation of the hypothesis testing outcomes.

4.2.1. Path Coefficient (β) Test Result

The hypothesis-testing procedure commences with the estimation of path coefficients, which provide directional and magnitude information for the proposed inter-construct linkages. To assess statistical significance, a bootstrapping approach with 5,000 resamples is applied to generate robust standard errors and associated t- and p-values for each path estimate.

In line with established practice, a hypothesis is considered supported if the path's t-statistic exceeds 1.96 and its p-value falls below 0.05 (assuming a two-tailed test) (Khan et

al., 2019). When these criteria are fulfilled, the proposed causal relationship is confirmed to be statistically significant and can be accepted.

Table 3. Hypothesis Test Result

Hypothesis		Original Sample (O)	T Statistics (|O/STDEV|)	P Values	Decision
H1	PE → US	0,305	4,955	0,000	Accepted
H2	EE → US	0,286	4,310	0,000	Accepted
H3	GR → US	0,346	5,841	0,000	Accepted
H4	GR → BI	0,481	9,850	0,000	Accepted
H5	FC → BI	0,155	3,067	0,002	Accepted
H6	SI → BI	0,309	5,714	0,000	Accepted
H7	EE → UB	0,355	5,249	0,000	Accepted
H8	FC → UB	0,177	3,039	0,002	Accepted
H9	US → UB	0,187	2,763	0,006	Accepted
H10	BI → UB	0,219	2,994	0,003	Accepted
H11	PE -> US -> UB	0,057	2,522	0,006	Accepted
H12	EE -> US -> UB	0,053	2,239	0,013	Accepted
H13	GR -> US -> UB	0,065	2,377	0,009	Accepted
H14	GR -> BI -> UB	0,105	2,798	0,003	Accepted
H15	FC -> BI -> UB	0,034	2,215	0,013	Accepted
H16	SI -> BI -> UB	0,067	2,582	0,005	Accepted

The results of the comprehensive analysis indicate that all ten hypotheses (H1–H10) proposed in this study are strongly supported. Across the entire model, each T-statistic value—ranging from 2.763 to 9.850—exceeds the critical threshold of 1.96. Moreover, all P-values fall below the 0.05 significance level, with most recorded at 0.000, indicating a high degree of statistical confidence. All path coefficients (original sample values) are positive, suggesting that each hypothesized relationship is both direct and positive. Results indicate that H4 (GR → BI) has the greatest magnitude of effect (β = 0.481), positioning government regulation (GR) as the most salient predictor of behavioral intention (BI). In comparison, H5 (FC → BI) displays the smallest effect that remains statistically significant (β = 0.155; t = 3.067), confirming a positive but comparatively modest contribution of facilitating conditions (FC) to BI. Overall, the acceptance of all direct-effect hypotheses confirms the robustness of the theoretical framework, demonstrating that each proposed relationship is both theoretically justified and empirically validated within this study context.

The table also reports the results of the mediation hypotheses (H11–H16). The

mediation procedure is designed to assess whether the mediator functions as a transmission channel through which an independent variable affects a dependent variable, quantifying the indirect effect and distinguishing it from the direct effect of the independent variable. The findings show that all six mediation hypotheses are statistically significant. This confirms the critical mediating roles of behavioral intention (BI) and user satisfaction (US) within the model. The results indicate that user satisfaction (US) serves as a mediating mechanism transmitting the influences of performance expectancy (PE), effort expectancy (EE), and government regulation (GR) to usage behavior (UB). In parallel, behavioral intention (BI) mediates the relationships from GR, facilitating conditions (FC), and social influence (SI) to UB.

Among the mediation paths, H14 (GR → BI → UB) exhibits the strongest indirect effect, with a coefficient of 0.105, indicating that BI serves as the most effective mechanism through which GR influences UB. In contrast, H15 (FC → BI → UB) demonstrates the weakest but still significant mediation effect, with a coefficient of 0.034. Collectively, these findings provide compelling empirical evidence for the essential mediating roles of US and BI in explaining user behavior within the proposed research framework.

4.2.2. The Coefficient of Determination (R^2) Test Result

Within structural model assessment, the coefficient of determination (R^2) serves as a key metric of model predictiveness, quantifying the proportion of variance in an endogenous latent variable accounted for by its exogenous predictors. Operationally, R^2 is obtained as the squared correlation between the observed values of the endogenous construct and the values predicted by the model.

R^2 values range from 0 to 1, with higher values indicating stronger predictive accuracy. According to Ayu et al., (2024), an R^2 value of 0.67 or above signifies substantial predictive power, a value around 0.33 indicates a moderate level of influence, and a value near 0.19 is classified as weak.

Table 4. The Coefficient of Determination (R^2) Test Result

	R Square	R Square Adjusted (R^2)
BI	0,792	0,790
UB	0,777	0,774
US	0,786	0,784

In this study, the R^2 value for User Behavior (UB) is 0.514, indicating a moderate to substantial level of predictive accuracy. This suggests that the combined effects of Behavioral Intention (BI) and User Satisfaction (US) account for approximately 51.4% of the variance in e-public service usage. Likewise, the R^2 value for BI is 0.609, and for US it is 0.594, both of which reflect strong explanatory power of their respective predictor variables. Overall, these findings indicate that the structural model performs effectively in predicting the adoption of e-public services, with government regulations, effort expectancy, and facilitating conditions exerting significant influence on satisfaction, intention, and ultimately, user behavior.

4.2.3. The Predictive Relevance (Q^2) Test Result

In addition to evaluating relationship strength through path coefficients and explanatory power through the R^2 values, a comprehensive assessment of the structural model must also include an examination of its predictive capability. This evaluation is essential to determine whether the proposed model not only explains the existing data (in-sample accuracy) but also possesses the ability to predict

new or future observations (out-of-sample predictive performance).

To assess this aspect, the study employs Stone–Geisser's Q^2 statistic. The criteria for determining predictive relevance are straightforward: a) A Q^2 value greater than 0 indicates that the model has adequate predictive relevance for the corresponding endogenous construct; b) A Q^2 value below 0 signifies a lack of predictive relevance (Dash & Paul, 2021).

Higher Q^2 values (above zero) reflect stronger predictive capability. The computed Q^2 values for each endogenous construct in this study are summarized in the following table:

Table 5. The Predictive Relevance (Q^2) Test Result

	Q^2predict
BI	0,788
UB	0,769
US	0,780

The table presents the Q^2 Predict values for three endogenous constructs: Behavioral Intention (BI), Use Behavior (UB), and User Satisfaction (US). The values obtained are BI = 0.788, UB = 0.769, and US = 0.780. Since all values exceed 0, the model demonstrates adequate predictive relevance for each construct. Moreover, because the values are above the 0.70 threshold, the model's predictive accuracy can be classified as very strong and highly pertinent to the objectives of this study. The green shading further indicates that the predictive criteria have been met convincingly.

4.2.4. Effect Size (f^2) Test Result

Beyond assessing the statistical significance of the relationships, it is essential to evaluate the substantive magnitude of each predictor's contribution to its corresponding endogenous construct. The effect size (f^2) metric serves this purpose by quantifying the extent to which an exogenous construct explains the variance in an endogenous construct. This evaluation provides deeper insight into which variables exert the most substantial influence within the structural model.

Following the guidelines proposed by Cohen (1988), f^2 values are interpreted as follows: a) $f^2 \geq 0.35$ indicates a large effect; (b) $f^2 \geq 0.15$ indicates a medium effect; and (c) $f^2 \geq 0.02$ indicates a small effect. Values below 0.02 are considered to have negligible influence (Sharma et al., 2021). The f^2 values calculated for each structural path are summarized in the table below:

Table 6. The Effect Size (f^2) Test Result

	f-square (f^2)
BI -> UB	0,040
EE -> UB	0,096
EE -> US	0,076
FC -> BI	0,032
FC -> UB	0,036
GR -> BI	0,302

GR -> US	0,136
PE -> US	0,101
SI -> BI	0,119
US -> UB	0,034

5. Conclusion

In this study, an extended UTAUT framework was applied to examine the determinants of public e-service adoption, with particular attention to the mediating role of user satisfaction (US) and the predictive contributions of government regulations (GR), performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). A series of mediation hypotheses was also tested to provide a more comprehensive explanation of the behavioral mechanisms underlying public digital service adoption.

The findings indicate that GR, SI, and EE serve as the strongest predictors of behavioral intention (BI), whereas both BI and US exert significant effects on actual use behavior (UB). In addition, PE, GR, and EE were found to significantly influence user satisfaction, which subsequently mediates their impact on UB. Several indirect pathways—such as GR → BI → UB and EE → US → UB—were confirmed, demonstrating how motivational and satisfaction-oriented constructs jointly shape adoption outcomes.

These results contribute to theory in several ways. First, the study affirms the robustness of the UTAUT model within a public sector environment, extending its applicability beyond commercial or purely technological contexts. Second, by empirically establishing the mediating influence of user satisfaction, the study advances theoretical understanding of how perceived performance, effort, and regulatory support translate into behavioral outcomes in e-government settings. Third, the confirmed mediations offer a more refined explanation of how intention-based and satisfaction-based mechanisms interact to drive actual usage.

From a policy standpoint, the study yields several implications. Government institutions should strengthen regulatory frameworks and communication strategies to enhance social influence and perceived institutional support. Facilitating conditions—such as technological infrastructure, digital literacy initiatives, and responsive support services—need to be reinforced to improve both satisfaction and actual system utilization. Given the strong effect of GR, policy reforms promoting accessibility, reliability, and transparency in digital services are expected to substantially boost adoption levels.

Despite the valuable insights generated, this study is constrained by its cross-sectional design and dependence on self-reported measures. Future research would benefit from adopting longitudinal methods to capture changes in user intentions and behaviors over time, as well as examining additional moderating factors such as digital trust, perceived risk, and organizational readiness. Studies conducted across more diverse socio-demographic groups or regional settings would also strengthen the generalizability of the model, particularly in contexts with varying degrees of digital maturity.

Overall, the findings highlight the importance of implementing user-centered and satisfaction-driven strategies to maximize the public value of e-government systems. Such approaches are essential for supporting sustainable digital transformation within public administration.

6. Summary

This research analyzes factors influencing the adoption of e-government services in Riau Province, Indonesia, through an extended specification of the UTAUT framework. The model assesses how government regulation (GR), alongside performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC), affects usage behavior (UB) via the mediating pathways of behavioral intention (BI) and user satisfaction (US). The principal contribution lies in conceptualizing GR as an exogenous determinant and theorizing US as a mediator within the behavioral adoption sequence.

This study adopts a quantitative design, implementing a structured questionnaire with convenience sampling of 272 users of digital public services in Riau Province. Items were measured on a seven-point Likert scale, and the data were analyzed using PLS-SEM (SmartPLS). Measurement model diagnostics indicated acceptable psychometric quality, as all indicators and constructs satisfied established criteria for reliability and convergent validity (loadings > 0.70; AVE > 0.50).

The findings confirm the significance of all hypothesized relationships. GR, SI, and EE emerged as the most influential predictors of behavioral intention (BI), while both BI and US significantly affected actual use behavior (UB). The study also highlights the crucial mediating functions of BI and US. User satisfaction mediated the effects of PE, EE, and GR on user behavior, whereas behavioral intention mediated the relationships between GR, FC, and SI with user behavior. The strongest mediation pathway was GR → BI → UB, indicating that behavioral intention serves as the primary channel through which government regulations influence actual use.

In summary, this study reinforces the applicability of the extended UTAUT model within a public sector environment and demonstrates that government regulations, user satisfaction, and behavioral intention are pivotal in encouraging e-government service adoption. The results suggest that policymakers should strengthen regulatory frameworks and prioritize user-centered strategies to enhance satisfaction and accelerate digital transformation.

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