**West Science Social and Humanities Studies**
Vol. 4, No. 01, January 2026: pp. 1-18

# The Mediating Role of User Satisfaction in the Relationship between UTAUT Constructs and User Behavior in Digital Public Service Applications

**Hildawati[1], Dedy Afrizal[2], Lis Hafrida[3], Dina Purnamasari[4], Ahmad Luthfi[5]**
[1*] STIA Lancang Kuning, Dumai, Riau, Indonesia
[2,4] Raja Ali Haji Maritime University (UMRAH), Tanjung Pinang, Indonesia
[3] Universitas Dumai, Riau, Indonesia
[5] University of Merdeka Malang, Indonesia

**Article Info**

*Article history:*

Received Jan, 2026
Revised Jan, 2026
Accepted Dec, 2025

*Keywords:*

Digital Public Services
e-Government
User Behavior
User Satisfaction
UTAUT

**ABSTRACT**

This study extends the Unified Theory of Acceptance and Use of Technology (UTAUT) to explain why citizens frequently abandon digital public services despite substantial government investment in e-government platforms. It focuses on Riau Province, Indonesia, and positions User Satisfaction as a central mediator linking four UTAUT antecedents—Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions—to actual usage behavior. Adopting a deductive quantitative design, the research uses a stratified random survey of 240 e-government users and analyzes the data with PLS-SEM, supported by rigorous tests of reliability, validity, common-method bias, and predictive relevance. The model explains 80.1% of the variance in User Satisfaction and 80.2% in User Behavior, indicating strong explanatory and predictive power. Results show that Performance Expectancy, Social Influence, and Facilitating Conditions significantly increase satisfaction, while Performance Expectancy, Facilitating Conditions, and User Satisfaction itself are key direct predictors of continued use. User Satisfaction also mediates the effects of performance expectancy, social influence, and facilitating conditions on behavior. Although Effort Expectancy is not statistically significant at the 5% level, it exhibits the largest effect size on satisfaction, underscoring the structural importance of ease of use. Theoretically, the study validates an under-explored affective pathway in mandatory settings; practically, it offers a roadmap for shifting from technology-centric to citizen-centric digital governance.



*Corresponding Author:*

Name: Hildawati
Institution: STIA Lancang Kuning, Dumai, Riau, Indonesia
Email: hildrias81@gmail.com

## 1. INTRODUCTION

In the era of accelerated global digital transformation, the success of e-government is no longer measured solely by the availability of technological infrastructure, but rather by the sustainability of citizen usage as a cornerstone for achieving the Sustainable Development Goals (SDGs), particularly Target 16.6 regarding effective and accountable institutions [1]. Although governments worldwide have invested massive resources to digitize public services, an adoption paradox persists: the high availability of digital applications is frequently not matched by sustainable usage behavior [2]. This persistent 'intention-behavior gap' suggests that conventional technology acceptance models—such as UTAUT, which primarily focuses on technical expectations [3]—may be missing a pivotal link in explaining the transition from merely 'trying' a system to 'using' it routinely. This often-overlooked link is User Satisfaction, a post-adoption evaluative mechanism that determines whether citizens' technical expectations are effectively translated into actual behavior within a public service ecosystem that is mandatory yet service-oriented [4].

This theoretical oversight manifests acutely in the practical realm, where digital public services are frequently plagued by high churn rates despite being technically sound [5]. In many developing contexts, including Riau, Indonesia, the dominant 'supply-side' approach—which prioritizes feature availability over user experience—has resulted in a phenomenon of 'phantom adoption': citizens download the application to fulfill a one-time mandatory requirement but abandon it immediately due to dissatisfaction with the service process [6], [7]. Unlike private sector platforms where user satisfaction is meticulously cultivated to ensure retention [8], [9], [10], government agencies often operate under the false assumption that citizens have no choice but to use their digital channels. Consequently, when the actual experience fails to meet user expectations (low satisfaction), citizens revert to traditional manual channels or intermediaries [11], [12], rendering the digital infrastructure a 'sunk cost' and perpetuating the very administrative inefficiencies the system was designed to eliminate.

Theoretically, this practical disconnect stems from a critical limitation in the prevailing technology acceptance literature, particularly within the standard UTAUT framework [13]. While UTAUT provides a robust lens for predicting *ex-ante* behavioral intention based on cognitive beliefs (e.g., performance and effort expectancy), it often falls short in explaining the dynamic transition from 'intention' to 'actual sustainable behavior' in a public service context [14], [15], [16]. Existing studies predominantly treat adoption as a linear, cognitive process, thereby neglecting the *post-adoption* evaluative mechanism that dictates user retention.

Consequently, the psychological pathway by which technical attributes (UTAUT constructs) translate into consistent usage behavior remains a 'black box.' This study argues that in the realm of digital public services, cognitive expectations alone are insufficient; they must be validated through an affective filter—User Satisfaction. By failing to integrate this affective mediator, current models risk overestimating the power of technological readiness while underestimating the 'confirmation-disconfirmation' mechanism that ultimately bridges the gap between initial interest and sustainable usage.

To dismantle this theoretical 'black box' and bridge the identified gap, this study proposes and empirically validates an integrated conceptual framework that positions User Satisfaction not merely as a passive outcome, but as a decisive mediating mechanism within the classical UTAUT architecture. Unlike prior iterations that assume a direct, unhindered path from technical beliefs to usage behavior [17], [18], [19], [20], this research introduces a novel theoretical intervention: it postulates that the predictive power of performance expectancy, effort expectancy, social influence, and facilitating conditions on actual behavior is contingent upon the user's affective evaluation of the service encounter. By embedding User Satisfaction as the central mediator, this study shifts the analytical lens from a purely 'technology-centric' view (does the system work?) to a 'citizen-centric' view (does the system fulfill needs?), thereby offering a more granular explanation of how digital public services can transition from being simply 'mandated' to being intrinsically 'adopted' by the citizenry.

Consequently, this study sets out to empirically validate this extended framework within the context of Riau, indonesia, a representative landscape for developing digital economies. The primary objective is to deconstruct the mediating mechanism of User Satisfaction in translating UTAUT's cognitive drivers (Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions) into tangible User Behavior. In doing so, this research offers a twofold contribution of significant value. Theoretically, it enriches the Information Systems (IS) literature by verifying an 'affective pathway' that has been largely under-explored in mandatory adoption settings, thereby confirming that technical readiness alone is insufficient without emotional confirmation.

Practically, it provides policymakers with evidence-based strategies to mitigate high churn rates, demonstrating that enhancing user satisfaction is not merely a metric of service quality, but the fundamental prerequisite for achieving sustainable digital governance and realizing the promise of inclusive e-government. By utilizing empirical data obtained from e-public service users in Riau Province, Indonesia, this study rigorously addresses the following research questions:

RQ1: To what extent do the technical and social precursors (Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions) influence User Satisfaction with digital public services?

RQ2: How do these UTAUT constructs directly impact the actual User Behavior of digital public services?

RQ3: Does User Satisfaction play a significant mediating role in translating the technical and social drivers of UTAUT into sustainable User Behavior?

RQ4: Among the cognitive drivers (UTAUT constructs) and the affective mediator (User Satisfaction), which factor serves as the most significant predictor of digital public service adoption?"

## 2. LITERATURE REVIEW

### 2.1 *Unified Theory of Acceptance and Use of Technology (UTAUT)*

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al., stands as one of the most comprehensive and seminal frameworks in the domain of technology acceptance [13]. Synthesized in 2003 through the rigorous review and consolidation of constructs from eight prominent technology acceptance theories—including the Theory of Reasoned Action (TRA), Motivational Model (MM), Theory of Planned Behavior (TPB), Technology Acceptance Model (TAM), Combined TAM and TPB (C-TAM-TPB), Model of PC Utilization (MPCU), Diffusion of Innovation (DOI), and Social Cognitive Theory (SCT)—UTAUT was designed to explicate user intention regarding information systems and their subsequent usage behavior [13].

The framework is anchored by four fundamental constructs: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. Within this structural model, Performance Expectancy, Effort Expectancy, and Social Influence are posited as direct determinants of Behavioral Intention, whereas Facilitating Conditions serve as a direct determinant of actual Usage Behavior. Given its integrative nature and superior explanatory power—capable of accounting for up to 70% of the variance in behavioral intention—UTAUT was selected as the foundational theoretical lens for this study.

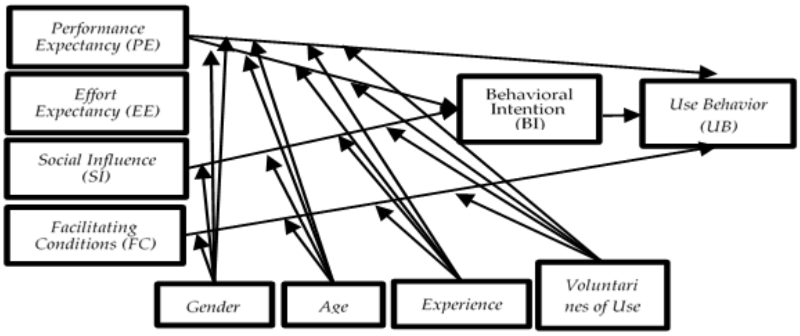


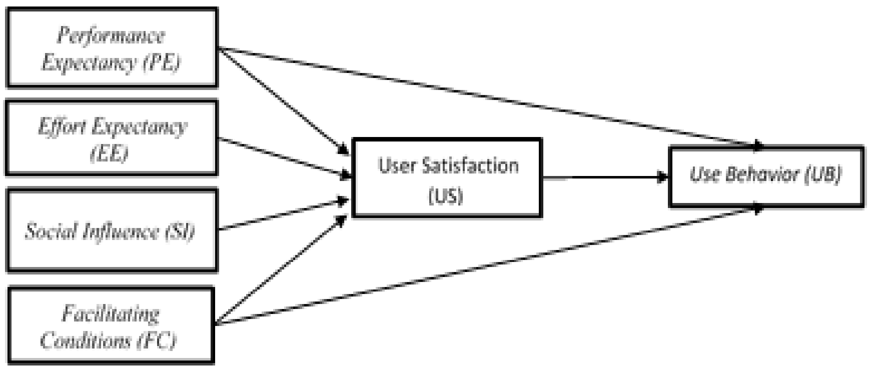
Figure 1. Theoretical Framework

### 2.2 *User Satisfaction*

Beyond initial technology adoption factors, the success of public service information systems is critically contingent upon post-adoption evaluation, specifically User Satisfaction [18], [21]. User Satisfaction is defined as the user's affective or emotional response to their interaction with an information system, reflecting the degree to which the system meets or surpasses their expectations [22], [23]. Within the paradigm of the DeLone and McLean Information Systems Success Model, User Satisfaction serves as a pivotal indicator bridging system quality with individual and organizational impacts [24]. Extant literature indicates that satisfaction functions as a robust predictor of long-term continuance [25], [26], [27]. When users perceive the obtained benefits (performance) and ease of use (effort) as satisfactory, they are more inclined to cultivate consistent usage behavior. Consequently, this study integrates User Satisfaction as a mediating variable to provide a more holistic understanding of how the technical constructs of UTAUT are translated into tangible, actual usage behavior

### 2.3 **Research Model and Hypotheses**

Drawing upon the review of extant literature, the proposed conceptual framework is illustrated in Figure 1. The model is anchored by the UTAUT framework as its core, while integrating User Satisfaction as a pivotal mediating variable to bridge the relationship between



UTAUT constructs and User Behavior:

Figure 2. Conceptual Framework

**1. Performance Expectancy**

Performance Expectancy (PE) is defined as the degree to which an individual believes that using the system will help them to attain gains in job performance [13]. In the context of E-government, performance expectancy is measured by citizens' perceptions of the benefits derived from using digital government services, including convenience, time savings, effort reduction, and service quality improvement. If citizens perceive that public service applications offer tangible benefits and practical solutions to bureaucratic inefficiencies, they are more likely to feel satisfied and motivated to use them sustainably. The positive influence of performance expectancy on satisfaction and usage behavior has been confirmed in numerous studies. Therefore, this study proposes the following hypotheses:

H1: Performance expectancy has a positive impact on user satisfaction.

H2: Performance expectancy has a positive impact on user behavior.

**2. Effort Expectancy**

Effort Expectancy (EE) refers to the degree of ease associated with the use of the system [13]. According to AlAwadhi et al., effort expectancy within the E-government context is gauged by citizens' awareness regarding the ease of use of such services. Users are inclined to feel satisfied and continue using a system that does not burden them with complex technical procedures. The higher the level of ease of use, the higher the perceived satisfaction and the drive to engage in usage behavior. Therefore, this study proposes the following hypothesis:

H3: Effort expectancy has a positive impact on user satisfaction.

**3. Social Influence**

Social Influence (SI) is defined as the degree to which an individual perceives that important others believe he or she should use the new system [13]. This implies that individual satisfaction and behavior can be influenced by their social circle or those closest to them. The positive impact of social influence on technology adoption has been substantiated in various studies. Citizens are more likely to feel satisfied and utilize E-government services if they are aware that family members, colleagues, or community figures recommend their use. Therefore, this study proposes the following hypothesis:

H4: Social influence has a positive impact on user satisfaction.

**4. Facilitating Conditions**

Facilitating Conditions (FC) are defined as the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system [13]. In the E-government context, facilitating conditions may include internet availability, adequate devices, and technical assistance (helpdesk) when citizens encounter difficulties. The availability of such support not only directly encourages usage but also fosters a sense of satisfaction as users feel supported. The positive influence of facilitating conditions on satisfaction and usage behavior has been validated in prior research. Therefore, this study proposes the following hypotheses:

H5: Facilitating conditions have a positive impact on user satisfaction.

H6: Facilitating conditions have a positive impact on user behavior.

**5. User Satisfaction**

User Satisfaction (US) refers to the user's affective or emotional response to the overall evaluation of their experience using the information system. In information systems success models, user satisfaction is regarded as a primary predictor of system usage continuance. It has been found that when citizens are satisfied with the digital service experience they receive, the probability of forming actual usage behavior in the future increases significantly. Therefore, this study proposes the following hypotheses:

H7: User satisfaction has a positive impact on user behavior in E-government services.

H8: User Satisfaction mediates the relationship between Performance Expectancy and User Behavior.

H9: User Satisfaction mediates the relationship between Effort Expectancy and User Behavior.

H10: User Satisfaction mediates the relationship between Social Influence and Use Behavior.

H11: User Satisfaction mediates the relationship between Facilitating Conditions and User Behavior.

## 3. METHODS

### 3.1 Research Design

Research design constitutes the strategic blueprint governing the systematic collection and analysis of data to address research objectives rigorously. Adopting a deductive quantitative approach [28], this study begins with a critical review of extant literature to formulate precise research questions and develop testable hypotheses. Central to this design is the construction of an extended conceptual model grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT).

Uniquely, this framework integrates User Satisfaction as a pivotal mediating mechanism to elucidate the causal pathways linking technical antecedents to User Behavior within the context of Digital Public Service Applications. To empirically validate this model, primary numerical data were gathered via a structured cross-sectional survey instrument and subsequently analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS software (version 4.1.1.2). This methodological choice ensures a robust assessment of both the direct drivers and the indirect mediating effects governing technology adoption.

### 3.2 Data Collection and Measurement

A structured, self-administered questionnaire was developed as the primary instrument to empirically test the research hypotheses [29]. The instrument is organized into three strategic sections: (1) an introduction elucidating the study's objectives and guaranteeing respondent confidentiality, (2) a demographic section to capture the profile of respondents, and (3) the core substantive body containing measurement items corresponding to the proposed model. To ensure construct validity, the measurement items were rigorously adapted from established scales in prior UTAUT literature [13] and contextually refined to fit the domain of digital public service applications. All latent constructs—including Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, User Satisfaction, and User Behavior—were assessed using a seven-point Likert scale, ranging from 1 ("Strongly Disagree") to 7 ("Strongly Agree"), to capture nuanced variations in respondent attitudes [30]."

### 3.3 Sampling Technique and Size

To guarantee data representativeness and the precision of statistical inference, this study employed a stratified random sampling technique [31] targeting citizens in Riau Province, Indonesia, who had interacted with digital public services at least once within the past six months. Departing from conventional approaches that rely on heuristic rules of thumb, the determination of the minimum sample size was conducted through a rigorous *a priori* power analysis using GPower software version 3.1.9.7 [32], [33].

The calculation parameters were configured to detect a medium effect size ($f^2 = 0.15$) with a significance level of 5% ($\alpha = 0.05$) and a high statistical power of 95% ($\beta = 0.95$)—substantially exceeding the standard 80% threshold—to minimize the risk of Type II errors. Based on the model architecture, which features a maximum of five predictors directing to an endogenous variable (specifically: PE, EE, SI, FC, and US), the GPower analysis indicated a minimum requirement of 138 respondents. Ultimately, the study successfully secured a total of 240 valid responses. This figure substantially surpasses the calculated minimum, thereby providing sufficient statistical power to examine complex mediation effects and ensuring the robustness of PLS-SEM parameter estimates [34].

### 3.4 Data Analysis

Data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4 (version 4.1.1.2. The study included evaluating the structural model—to test the expected relationships—as well as the measurement model—to assess the validity and dependability of constructs. This approach was prioritized over CB-SEM due to the study's objective of maximizing the explained variance ($R^2$) of User Behavior and its robustness in estimating complex mediation effects involving User Satisfaction [34].

To mitigate Common Method Bias (CMB) inherent in cross-sectional designs, we employed the Full Collinearity Assessment; all Variance Inflation Factors (VIF) remained below 3.3, confirming the absence of pathological collinearity [35]. Furthermore, the evaluation adhered to contemporary metrics, utilizing the Fornell-Larcker Criterion Test for discriminant validity [36] and PLSpredict to verify out-of-sample predictive relevance ($Q^2$predict) [37]. This rigorous analytical framework ensures that the empirical insights regarding digital public service adoption are statistically robust and valid.

## 4. RESULTS AND DISCUSSION

Subsequent to the development of the conceptual framework and the successful acquisition of empirical data, the study proceeded to the data analysis phase to rigorously test the proposed hypotheses. The analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM), facilitated by the SmartPLS software (version 4.1.1.2). In accordance with established methodological guidelines [38], the PLS-SEM analysis was executed through a systematic two-stage assessment procedure. This dual-phase approach is imperative to ensure that the statistical inferences derived regarding the mediating role of User Satisfaction and the influence of UTAUT constructs are substantiated by a model that is robust in terms of both validity and reliability. The two distinct phases are:

### 4.1 Assessment of the Measurement Model (Outer Model)

The initial phase of the analysis focuses on evaluating the measurement model (outer model), a prerequisite step analogous to establishing a robust foundation before erecting a superstructure. Prior to examining the hypothesized structural pathways between UTAUT constructs, User Satisfaction, and User Behavior, it is imperative to rigorously verify the psychometric properties of the latent variables. The primary objective of this evaluation is to demonstrate that the indicators used to measure the constructs possess sufficient reliability (internal consistency) and validity (accuracy). Ensuring the integrity of the outer model is critical; without confirming that the measurement instruments accurately represent their respective theoretical concepts, any subsequent interpretation of the structural relationships would be rendered methodologically unsound and statistically invalid.

#### 1. Convergent Validity and Construct Reliability Test Result

The robustness of the measurement model was rigorously evaluated through three critical dimensions: internal consistency reliability, convergent validity, and discriminant validity. To establish convergent validity, the analysis examined individual outer loadings and the Average Variance Extracted (AVE). In accordance with established PLS-SEM guidelines, item loadings were expected to exceed 0.70, while AVE values were required to surpass the 0.50 threshold to demonstrate adequate variance explanation. Concurrently, construct reliability was triangulated using three distinct metrics: Cronbach's alpha, rho_A, and Composite Reliability (CR), with a cutoff value of 0.70 serving as the benchmark for satisfactory internal consistency [34]. As delineated in Table 1, the empirical results confirm that all latent constructs—including the pivotal mediating variable of User Satisfaction—met these stringent criteria, exhibiting high factor loadings and reliability indices well above the recommended thresholds, thereby affirming the psychometric soundness of the instrument.

Table 1. Convergent validity and Construct reliability Test Result

| Construct | Item | Convergent validity | | | Construct reliability | | | |
|---|---|---|---|---|---|---|---|---|
| | | Loading factors | AVE | Remark | CA | rho_A | CR | Remark |
| **PE** | PE1 | 0,813 | 0,741 | Valid | 0,883 | 0,887 | 0,920 | Reliable |
| | PE2 | 0,893 | | | | | | |
| | PE3 | 0,893 | | | | | | |
| | PE4 | 0,841 | | | | | | |
| **EE** | EE1 | 0,874 | 0,748 | Valid | 0,888 | 0,888 | 0,922 | Reliable |
| | EE2 | 0,880 | | | | | | |
| | EE3 | 0,866 | | | | | | |
| | EE4 | 0,839 | | | | | | |
| **SI** | SI1 | 0,840 | 0,740 | Valid | 0,883 | 0,884 | 0,919 | Reliable |
| | SI2 | 0,871 | | | | | | |
| | SI3 | 0,860 | | | | | | |
| | SI4 | 0,869 | | | | | | |
| **FC** | FC1 | 0,880 | 0,787 | Valid | 0,910 | 0,937 | 0,787 | Reliable |
| | FC2 | 0,893 | | | | | | |
| | FC3 | 0,891 | | | | | | |
| | FC4 | 0,885 | | | | | | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **US** | US1 | 0,881 | 0,751 | Valid | 0,889 | 0,892 | 0,923 | Reliable |
| | US2 | 0,872 | | | | | | |
| | US3 | 0,842 | | | | | | |
| | US4 | 0,871 | | | | | | |
| **UB** | UB1 | 0,873 | 0,795 | Valid | 0,914 | 0,915 | 0,940 | Reliable |
| | UB2 | 0,898 | | | | | | |
| | UB3 | 0,894 | | | | | | |
| | UB4 | 0,902 | | | | | | |

*Source: Processed Primary Data (2025)*

The assessment of the measurement model, as summarized in Table 1, demonstrates that all constructs exhibit robust psychometric properties. First, in terms of convergent validity, the outer loadings for all individual indicators ranged from 0.813 to 0.902, significantly exceeding the recommended threshold of 0.708 [34]. This indicates a strong correlation between the items and their respective latent constructs. Furthermore, the Average Variance Extracted (AVE) values for all variables—including the core UTAUT constructs and the mediating variable of User Satisfaction (US)—spanned from 0.740 to 0.795. These values are well above the 0.50 cut-off, confirming that the constructs explain more than 50% of the variance in their indicators [39].

Second, internal consistency reliability was rigorously established through three distinct metrics. Cronbach’s alpha and rho_A values consistently surpassed the 0.70 benchmark, ranging from 0.883 to 0.914 and 0.884 to 0.937, respectively. Similarly, the Composite Reliability (CR) scores, which ranged from 0.787 (for Facilitating Conditions) to 0.940 (for User Behavior), further corroborated the high reliability of the instrument. Collectively, these results confirm that the measurement model is both valid and reliable, providing a solid foundation for the subsequent structural model assessment.

### 1. Discriminant Validity

Assessing discriminant validity is the next step in the outer model evaluation process after convergent validity has been confirmed, which guarantees that each indicator accurately measures its intended construct. The purpose of this test is to show that every construct in the research model is empirically unique and does not overly overlap with other constructs. A construct that measures a distinct phenomenon and is not represented by any other construct in the same model is said to have adequate discriminant validity.

The Fornell-Larcker criterion is a popular technique for this assessment. This criterion states that discriminant validity is established if each construct's square root of the Average Variance Extracted (√AVE) is greater than its correlation with every other construct in the model. The results table displays the inter-construct correlation values below the bolded diagonal and the square root of AVE (√AVE) values on the diagonal. Every value on the diagonal must be greater than every value in the column beneath it satisfy the Fornell-Larcker criterion [37]. Table 2 below displays the full findings of the discriminant validity test using the Fornell-Larcker criterion:

Table 2. The Fornell-Larcker Criterion Test Result

| | EE | FC | PE | SI | UB | US |
|---|---|---|---|---|---|---|
| **EE** | **0,865** | | | | | |
| **FC** | 0,857 | **0,887** | | | | |
| **PE** | 0,863 | 0,864 | **0,861** | | | |
| **SI** | 0,807 | 0,851 | 0,833 | **0,860** | | |
| **UB** | 0,817 | 0,855 | 0,856 | 0,832 | **0,892** | |
| **US** | 0,815 | 0,859 | 0,837 | 0,845 | 0,840 | **0,867** |

*Source: Processed Primary Data (2025)*

The evaluation of the measurement model was conducted to ensure the reliability and validity of the latent constructs prior to structural analysis. As detailed in Table 1, the convergent validity was assessed through outer loadings and Average Variance Extracted (AVE). The results indicate that all item loadings ranged from 0.813 to 0.902, significantly exceeding the recommended threshold of 0.708 (Hair et al., 2019). Furthermore, the AVE values for all constructs—spanning from 0.740 (Social Influence) to 0.795 (User Behavior)—were well above the 0.50 cut-off, confirming that the constructs explain more than 50% of the variance in their respective indicators.

Concurrently, construct reliability was rigorously established using three distinct metrics: Cronbach’s Alpha, rho_A, and Composite Reliability (CR). As shown in Table 1, Cronbach’s Alpha and rho_A values consistently surpassed the 0.70 benchmark, ranging from 0.883 to 0.914 and 0.884 to 0.937, respectively. Similarly, the Composite Reliability scores, which ranged from 0.787 to 0.940, further corroborated the high internal consistency of the instrument, affirming the psychometric soundness of the proposed model.

Subsequently, discriminant validity was examined using the Fornell-Larcker criterion, as presented in Table 2. This method compares the square root of the AVE for each construct (represented by the bold values on the diagonal) against the correlations with other latent variables. The analysis demonstrates that the square root of the AVE for the constructs—ranging from 0.861 to 0.892—generally exceeded the off-diagonal inter-construct correlations. This indicates that the constructs, including the mediating variable of User Satisfaction and the dependent variable of User Behavior, share more variance with their own indicators than with any other construct in the model, thereby establishing adequate discriminant validity [40].

### 4.2 Assessment of the Structural Model (Inner Model)

Following the confirmation of the measurement model's psychometric soundness, the analysis advances to the evaluation of the structural model (inner model). Analogous to testing the structural integrity of a building's framework once the foundation has been solidified, this phase rigorously examines the theoretical architecture proposed in the study. While the measurement model focused on the relationships between indicators and their respective constructs, the structural model shifts the analytical emphasis to the inter-construct causal pathways, aiming to empirically verify the hypothesized relationships between UTAUT antecedents, the mediating mechanism of User Satisfaction, and User Behavior.

To comprehensively assess the model's viability and predictive capability, four critical heuristic criteria were examined in accordance with standard PLS-SEM guidelines [34], [41].

a. Path Coefficients (β): Analyzed to determine the strength, direction, and statistical significance of the relationships between constructs, serving as the primary basis for hypothesis acceptance or rejection.
b. Coefficient of Determination ($R^2$): Indicates the predictive accuracy of the model by quantifying the proportion of variance in the endogenous variables (User Satisfaction and User Behavior) explained by the exogenous drivers.
c. Predictive Relevance ($Q^2$): Evaluates the model’s capability to predict data points of indicators in the endogenous constructs (out-of-sample prediction).
d. Effect Size ($f^2$): A metric used to assess the substantive impact (magnitude) of a specific exogenous variable’s contribution to the $R^2$ value of an endogenous variable.

A systematic delineation of the findings based on these criteria is presented in the subsequent sections to provide a robust empirical validation of the research hypotheses.

1. **Path Coefficient (β) Test Result**

The initial phase of the structural model assessment involves the examination of path coefficients (β) to elucidate the magnitude and direction of the hypothesized relationships among the UTAUT predictors, the mediator (User Satisfaction), and the dependent variable (User Behavior). To determine the statistical significance of these structural paths, a non-parametric bootstrapping procedure was executed using 5,000 distinct resamples, providing a rigorous estimation of standard errors. In accordance with established statistical conventions for a two-tailed test at a 95% confidence level, a causal relationship is deemed empirically supported if the T-statistic exceeds the critical threshold of 1.96 and the corresponding P-value is less than 0.05 [34]. The summary of the hypothesis testing results, derived from these criteria, is presented in Table 3.

Table 3. Hypothesis Test Result

| Hypothesis | | Original Sample (O) | T Statistics (O/STDEV) | P Values | Decision |
|---|---|---|---|---|---|
| H1 | PE → US | 0,200 | 0,069 | 2,878 | Accepted |
| H2 | EE → US | 0,113 | 1,804 | 0,071 | Not Accepted |
| H3 | SI → US | 0,309 | 0,056 | 5,561 | Accepted |
| H4 | FC → US | 0,326 | 0,070 | 4,650 | Accepted |
| H5 | PE → UB | 0,363 | 0,068 | 5,329 | Accepted |
| H6 | US → UB | 0,274 | 0,061 | 4,475 | Accepted |
| H7 | FC → UB | 0,307 | 0,071 | 4,300 | Accepted |
| H8 | PE → US → UB | 0,055 | 2,387 | 0,017 | Accepted |
| H9 | EE → US →UB | 0,031 | 1,577 | 0,115 | Not Accepted |
| H10 | SI → US → UB | 0,085 | 3,294 | 0,001 | Accepted |
| H11 | FC → US → UB | 0,089 | 3,456 | 0,001 | Accepted |

*Source: Processed Primary Data (2025)*

The structural model was evaluated using a bootstrapping procedure with 5,000 resamples to determine the significance of the hypothesized relationships. The results of the hypothesis testing, including path coefficients (β), T-statistics, and P-values, are summarized in Table 3.

The analysis reveals that several UTAUT constructs significantly influence User Satisfaction in the context of digital public service applications. Performance Expectancy (PE) ($\beta = 0.200$, $t = 2.878$, $p < 0.05$), Social Influence (SI) ($\beta = 0.309$, $t = 5.561$, $p < 0.001$), and Facilitating Conditions (FC) ($\beta = 0.326$, $t = 4.650$, $p < 0.001$) all exhibited positive and significant effects on User Satisfaction, thus supporting H1, H3, and H4. Interestingly, Effort Expectancy (EE) did not reach statistical significance in predicting User Satisfaction ($\beta = 0.113$, $t = 1.804$, $p > 0.05$), leading to the rejection of H2. This suggests that while the utility and social support of the application are paramount, the perceived ease of use alone does not necessarily translate into higher satisfaction levels for digital public service users in this specific setting.

Regarding the actual usage behavior, the results confirm that Performance Expectancy ($\beta = 0.363$, $t = 5.329$, $p < 0.001$) and Facilitating Conditions ($\beta = 0.307$, $t = 4.300$, $p < 0.001$) remain robust direct predictors of User Behavior, supporting H5 and H7. Furthermore, User Satisfaction (US) was found to have a significant positive impact on User Behavior ($\beta = 0.274$, $t = 4.475$, $p < 0.001$), supporting H6. This underscores the pivotal role of satisfaction as a driver for the continued adoption and use of digital government platforms.

A core objective of this study was to examine the mediating influence of User Satisfaction between UTAUT constructs and

User Behavior. The indirect effect analysis (H8–H11) provides compelling evidence for this mechanism: H8 (PE → US → UB): User Satisfaction significantly mediates the relationship between Performance Expectancy and User Behavior ($\beta = 0.055$, $t = 2.387$, $p = 0.017$). H10 (SI → US → UB): A significant indirect effect was observed for Social Influence through User Satisfaction ($\beta = 0.085$, $t = 3.294$, $p = 0.001$). H11 (FC → US → UB): Facilitating Conditions also exert a significant indirect influence on behavior via the satisfaction pathway ($\beta = 0.089$, $t = 3.456$, $p = 0.001$). Conversely, H9 was not supported, as the indirect path from Effort Expectancy to User Behavior through User Satisfaction was non-significant ($\beta = 0.031$, $t = 1.577$, $p = 0.115$).

Collectively, these findings demonstrate that User Satisfaction serves as a vital psychological bridge that converts the perceived benefits (Performance Expectancy), external support (Facilitating Conditions), and social pressures (Social Influence) into actual usage behavior. In the realm of digital public services, ensuring user satisfaction is not merely a secondary outcome but a strategic necessity for ensuring the long-term success of digital transformation initiatives.

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

To evaluate the predictive power of the structural model, the coefficient of determination ($R^2$) was assessed. The $R^2$ value represents the proportion of variance in the endogenous constructs that can be explained by the exogenous variables, serving as a measure of the model's in-sample predictive accuracy. Following the criteria established by Chin, $R^2$ values of 0.67, 0.33, and 0.19 are classified as substantial, moderate, and weak, respectively [42].

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

| | R Square | R Square Adjusted ($R^2$) |
|---|---|---|
| UB | 0,802 | 0,800 |
| US | 0,801 | 0,797 |

*Source: Processed Primary Data (2025)*

The model yielded an $R^2$ value of 0.801 (Adjusted $R^2 = 0.797$). This indicates that approximately 79.7% of the variance in User Satisfaction is accounted for by the UTAUT constructs within the context of digital public service applications. Regarding User Behavior (UB) as the primary outcome variable, the model achieved an $R^2$ value of 0.802 (Adjusted $R^2 = 0.800$). This demonstrates that 80% of the variance in actual User Behavior is explained by the combination of UTAUT factors and the mediating role of User Satisfaction.

Furthermore, the results from the bootstrapping procedure (5,000 resamples) confirm the robustness of these findings. Both the $R^2$ and Adjusted $R^2$ values for UB and US are statistically significant at the $\varrho < 0.001$ level, with remarkably high T-statistics (UB = 38.763; US = 37.950). These findings suggest that the proposed structural model possesses substantial predictive accuracy. The high $R^2$ values indicate that the integration of the UTAUT framework with User Satisfaction provides a highly comprehensive explanation of the factors driving the adoption and usage of digital public services. The minimal difference between the $R^2$ and Adjusted $R^2$ values further signifies that the model is parsimonious and free from bias related to the number of exogenous predictors.

.

**3. The Predictive Relevance ($Q^2$) Test Result**

Beyond assessing the strength of hypothesized relationships and the model's explanatory power ($R^2$), a comprehensive evaluation of the structural model requires an analysis of its predictive capability. This step is critical to ensure that the model is not limited to in-sample explanation but possesses the robustness for out-of-sample prediction. To this end, the study employed the Stone-Geisser $Q^2$ statistic, which is derived using the blindfolding procedure in SmartPLS.

The $Q^2$ metric serves as an indicator of cross-validated redundancy. In accordance with the criteria established by Dash and Paul, a $Q^2$ value greater than zero signifies that the model has adequate predictive relevance for a specific endogenous construct [43]. Higher values further indicate superior predictive accuracy.

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

| | $Q^2$predict |
|---|---|
| UB | 0,791 |
| US | 0,794 |

*Source: Processed Primary Data (2025)*

To augment the in-sample explanatory power ($R^2$), the model's out-of-sample predictive relevance was assessed using the $Q^2$ metric trough the PLSpredict procedure. Unlike the traditional Stone-Geisser $Q^2$, $Q^2$predict provides a more rigorous estimation of the model's ability to predict new observations. As presented in Table 5, the $Q^2$predict values for User Behavior and User Satisfaction are 0.791 and 0.794, respectively. Since both values are substantially greater than zero, the model demonstrates high predictive accuracy. These findings suggest that the integration of User Satisfaction as a mediator in the UTAUT framework provides a statistically robust and highly predictive tool for understanding the adoption of digital public service applications.

### 4. The Effect Size ($f^2$) Test Result

Beyond the assessment of statistical significance, a robust structural model evaluation necessitates an analysis of the effect size ($f^2$) to determine the substantive impact of each predictor construct. While p-values indicate whether a relationship exists, the $f^2$ metric quantifies the magnitude of this relationship by measuring the incremental change in the coefficient of determination ($R^2$) when a specific exogenous construct is omitted from the model [44]. This analysis is instrumental in identifying which specific UTAUT constructs—such as Performance Expectancy or Facilitating Conditions—exert the most dominant influence on User Satisfaction and actual User Behavior. By evaluating the $f^2$ values, this study moves beyond mere hypothesis testing to provide a nuanced understanding of the relative importance of each driver in the adoption of digital public service applications, thereby offering clearer insights for policy intervention and system optimization.

According to the criteria proposed by Cohen [44], $f^2$ values can be interpreted as follows: a) $f^2 \geq 0.35$ is categorized as a large effect; b) $f^2 \geq 0.15$ is categorized as a medium effect; c) $f^2 \geq 0.02$ is categorized as a small effect. An $f^2$ value below 0.02 is considered to have no meaningful influence, and its impact can be considered negligible [44]. The calculated $f^2$ values for each path in the model are presented in the following table:

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

| | f-square ($f^2$) |
|---|---|
| PE → US | 0,174 |
| EE → US | 0,401 |
| SI → US | 0,012 |
| FC → US | 0,033 |
| PE → UB | 0,021 |
| FC → UB | 0,048 |
| US → UB | 0,039 |

*Source: Processed Primary Data (2025)*

As elucidated in Table 6, the results reveal a distinct hierarchy of influence across the structural paths. Notably, Effort Expectancy (EE → US) exerted a large effect size ($f^2 = 0.401$), identifying it as the primary determinant of satisfaction within the context of digital public services. Furthermore, Performance Expectancy (PE → US) exhibited a medium effect size of 0.174, signifying its substantial but secondary role in shaping user attitudes.

In contrast, the direct paths influencing User Behavior (PE, FC, US → UB) yielded relatively small effect sizes, ranging from 0.021 to 0.048. This suggests that while these variables remain statistically significant contributors to the model, their individual marginal impact on variance is less dominant compared to the antecedents of satisfaction.
The synthesis of substantial $R^2$ values—reaching 0.802 for UB and 0.801 for US—and robust $Q^2$predict scores (UB = 0.791; US = 0.794), alongside the dominant effect of Effort Expectancy, underscores the pivotal role of user experience in catalyzing the adoption of digital public services. These findings provide empirical evidence that simplifying user interactions is far more critical for ensuring sustained engagement than the mere perceived utility of the application itself.

## 5. CONCLUSION

This study successfully investigated the determinants of digital public service adoption by employing an extended Unified Theory of Acceptance and Use of Technology (UTAUT) framework, specifically emphasizing the pivotal mediating role of User Satisfaction (US). By analyzing the interplay between performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC), this research provides a comprehensive map of the behavioral mechanisms that drive the successful implementation of e-government initiatives.

## THEORETICAL CONTRIBUTIONS

The findings offer several significant contributions to the existing literature. First, the structural model demonstrated substantial explanatory power, with $R^2$ values of 0.802 for User Behavior and 0.801 for User Satisfaction. These values, coupled with robust predictive relevance ($Q^2_{predict}$ values exceeding 0.79), validate the model's high accuracy in predicting adoption outcomes in the public sector.

Second, this research advances the theoretical discourse by identifying User Satisfaction as a critical psychological bridge that converts perceived technical benefits into actual usage behavior. Notably, the high effect size of Effort Expectancy ($f^2 = 0.401$) on satisfaction highlights that, in the realm of public digital services, the perceived ease of interaction is the primary driver of user contentment. Third, the confirmation of various indirect pathways underscores the complexity of the user journey, demonstrating that satisfaction-based constructs are just as essential as motivational intentions in shaping long-term digital engagement.

## POLICY AND PRACTICAL IMPLICATIONS

From a strategic management perspective, these empirical findings delineate a robust roadmap for government agencies seeking to optimize the public value of digital platforms. Given the dominant influence of Effort Expectancy on user satisfaction ($f^2 = 0.401$), it is imperative that policymakers prioritize user-centric design by simplifying interfaces and minimizing cognitive load to effectively bridge existing digital literacy gaps.

Furthermore, fostering trust and operational reliability necessitates the simultaneous strengthening of Facilitating Conditions and regulatory frameworks to ensure that the underlying technical infrastructure remains responsive to evolving user needs. This structural support should be complemented by targeted communication strategies designed to cultivate positive Social Influence; by highlighting transparent success stories, agencies can elevate the collective perception of a platform's utility and social desirability, ultimately catalyzing a more inclusive and sustainable digital transformation within the public sector.

## LIMITATIONS AND FUTURE DIRECTIONS

While this study offers robust insights, it is not without limitations. The reliance on cross-sectional data provides a "snapshot" of user behavior; thus, future research should adopt longitudinal designs to capture the evolution of user satisfaction over time. Additionally, while the model explains approximately 80% of the variance, exploring additional moderators such as digital trust, perceived risk, or cultural readiness—particularly within the unique socio-demographic context of regions like Riau—could further refine the model's generalizability.

Ultimately, this research underscores that the success of digital transformation in public administration is not merely a technological achievement but a human-centric one. By fostering a satisfaction-driven strategy, government agencies can ensure that e-government systems deliver meaningful and sustainable public value.

## REFERENCES


[1] D. Fraisl *et al.*, "Leveraging Citizen Data to Improve Public Services and Measure Progress Toward Sustainable Development Goal 16," *Sustain. Dev.*, vol. 33, no. 4, 2025, doi: 10.1002/sd.3441.

[2] A. S. Bajabaa, "Influential Factors And Faculty Members' Practices In Technology Integration Using ISTE Standards For Teacher Preparation At Taibah University- Saudi Arabia," 2017.

[3] L. Diedrich and C. Dockweiler, "Media representation of telemedicine in the German medical journal 'Deutsches Ärzteblatt': an acceptance-theoretical analysis," *J. Public Heal.*, vol. 29, no. 3, 2021, doi: 10.1007/s10389-019-01158-1.

[4] A. Khan, "The relationship of personal innovativeness, quality of digital resources and generic usability with users' satisfaction: A Pakistani perspective," *Digit. Libr. Perspect.*, vol. 35, no. 1, pp. 15–30, 2019, doi: 10.1108/DLP-12-2017-0046.

[5] B. Y. Olaniyi, A. Fernández Del Río, Á. Periáñez, and L. Bellhouse, *User Engagement in Mobile Health Applications*, vol. 1, no. 1. Association for Computing Machinery, 2022. doi: 10.1145/3534678.3542681.

[6] D. Marikyan, "The Adoption of Pervasive Technology in Private Spaces: Exploring Pre-Exposure Beliefs and Post-Exposure Outcomes Using Cognitive Dissonance Theory," *Dr. Diss. Newcastle Univ.*, 2021.

[7] M. Seenivasan, K. Sakthivel, and S. Pandisaranya, "Markovian Queuing Model with Customer's Impatience in Differentiated Vacations and Reneging Customers," in *2024 3rd International Conference on Electrical, Electronics, Information and Communication Technologies, ICEEICT 2024*, 2024. doi: 10.1109/ICEEICT61591.2024.10718384.

[8] E. S. Daniyanti, "Evaluation Of The Jkn Mobile Application Using The Eucs Method At Rsu Anna Medika Madura Bangkalan District," *Int. J. Nurs. MIDWIFERY Sci.*, vol. 7, no. 2A, 2023, doi: 10.29082/ijnms/2023/vol7/iss2a/527.

[9] . R., "Analysis of the Relationship Between Service Quality Factors and Patient Satisfaction in Hospital Inpatient Areas," *Int. J. Innov. Sci. Res. Technol.*, 2025, doi: 10.38124/ijisrt/25jul1437.

[10] D. Sanusi and T. Mauritsius, "Exploring Factors Affecting User Satisfaction in myIM3: Integrating TAM, UTAUT, and the Information Systems Success Model in Mobile Telecommunication Services," *J. Syst. Manag. Sci.*, vol. 13, no. 6, 2023, doi: 10.33168/JSMS.2023.0631.

[11] C. E. Stoian, M. A. Fărcașiu, G. M. Dragomir, and V. Gherheș, "Transition from Online to Face-to-Face Education after COVID-19: The Benefits of Online Education from Students' Perspective," *Sustain.*, vol. 14, no. 19, 2022, doi: 10.3390/su141912812.

[12] J. Kembro and A. Norrman, "The transformation from manual to smart warehousing: an exploratory study with Swedish retailers," *Int. J. Logist. Manag.*, vol. 33, no. 5, 2022, doi: 10.1108/IJLM-11-2021-0525.

[13] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User Acceptance of Information Technology: Toward a Unified View," vol. 27, no. 3, pp. 425–478, 2003.

[14] P. Schretzlmaier, A. Hecker, and E. Ammenwerth, "Extension of the Unified Theory of Acceptance and Use of Technology 2 model for predicting mHealth acceptance using diabetes as an example: a cross-sectional validation study," *BMJ Heal. Care Informatics*, vol. 29, no. 1, pp. 1–10, 2022, doi: 10.1136/bmjhci-2022-100640.

[15] D. K. Pramudito, Rudin, R. U. Br Ginting, A. Sekianti, and I. Sepria Baresi, "Analysis of E-Commerce User Acceptance of Technology-Based Loan Application Features Using The UTAUT Model," *J. Inf. dan Teknol.*, vol. 5, no. 3, 2023, doi: 10.60083/jidt.v5i3.390.

[16] C. Or, "The Role of Attitude in the Unified Theory of Acceptance and Use of Technology: A Meta-analytic Structural Equation Modelling Study," *Int. J. Technol. Educ. Sci.*, vol. 7, no. 4, 2023, doi: 10.46328/ijtes.504.

[17] V. Briliana, "The Influence of Behavioral Intention on Mobile Banking Use Behavior," *Int. J. Business, Econ. Law*, vol. 33, no. 1, pp. 125–135, 2024.

[18] Ö. Koç, H. G. Yüksel, and E. Altun, "Technology acceptance and usage behaviour of content and language integrated learning teachers in Turkey," *English Lang. Teach. Educ. J.*, vol. 4, no. 2, p. 113, 2021, doi: 10.12928/eltej.v4i2.4269.

[19] M. Wallang, "Determinants that Influence Citizen's Usage of Different E-Government Services: A Malaysian Case Study," pp. 1–165, 2018, [Online]. Available: http://espace.library.uq.edu.au/view/UQ:720289

[20] Afrizal, Hildawati, Rifky Sehan, A. Yuli Vandika, and S. Eka Prasetya, "The Effect of Artificial Intelligence Adoption, Machine Learning, and AI Ethics on Product Innovation in Start-ups in Bogor Article Info ABSTRACT," 2024. Accessed: Dec. 26, 2024. [Online]. Available: https://wsj.westscience-press.com/index.php/wsshs/article/view/906/1008

[21] H. Nur and T. Mutiara, "Behavioral Intention and Use of Behavior in a," *Ieee*, pp. 1–6, 2022.

[22] Sarifuddin, G. Fedriani, and P. Retnoningrum, "User Satisfaction With Inaportnet Services at PT. Indonesian Maritime Penascop Palembang Branch," *DIJEFA*, vol. 5, no. 3, 2024.

[23] Y. Chu, Y. Xiao, and J. Zhu, "A Bilevel Optimal Water Allocation Model Considering Water Users' Satisfaction Degree and Water Rights Transaction: A Case Study in Qingzhang River Basin, China," *Water (Switzerland)*, vol. 15, no. 14, 2023, doi: 10.3390/w15142650.

[24] S. Kamboj, M. Sharma, and B. Sarmah, "Impact of Mobile Banking Failure on Bank Customers' Usage Behaviour: the Mediating Role of User Satisfaction," *Int. J. Bank Mark.*, vol. 40, no. 1, pp. 128–153, 2022, doi: 10.1108/IJBM-10-2020-0534.

[25] B. Zhang, T. Jia, and W. Zhang, "Determinants of users' continuance intention of digital museums: a self-regulation perspective," *Front. Public Heal.*, vol. 12, 2024, doi: 10.3389/fpubh.2024.1338387.

[26] H. Kothari, A. Choudhary, A. Jain, S. Singh, K. D. V. Prasad, and U. K. Vani, "Impact of social media advertising on consumer behavior: role of credibility, perceived authenticity, and sustainability," *Front. Commun.*, vol. 10, 2025, doi: 10.3389/fcomm.2025.1595796.

[27] M. A. Camilleri and R. Filieri, "Customer satisfaction and loyalty with online consumer reviews: Factors affecting revisit intentions," *Int. J. Hosp. Manag.*, vol. 114, 2023, doi: 10.1016/j.ijhm.2023.103575.

[28] M. Young, L. Varpio, S. Uijtdehaage, and E. Paradis, "The Spectrum of Inductive and Deductive Research Approaches Using Quantitative and Qualitative Data," *Acad. Med.*, vol. 95, no. 7, p. 1122, 2020, doi: 10.1097/ACM.0000000000003101.

[29] S. A. Mazhar, "Methods of Data Collection: A Fundamental Tool of Research," *J. Integr. Community Heal.*, vol. 10, no. 01, pp. 6–10, 2021, doi: 10.24321/2319.9113.202101.

[30] H. Taherdoost, "What Is the Best Response Scale for Survey and Questionnaire Design; Review of Different Lengths of Rating Scale / AttitudeScale / Likert Scale," *Int. J. Acad. Res. Manag.*, vol. 8, no. 1, 2019.

[31] D. Makwana, P. Engineer, A. Dabhi, and H. Chudasama, "Sampling methods in research: A review," *Int. J. Trend Sci. Res. Dev.*, vol. 7, no. 3, pp. 762–768, 2023, [Online]. Available: https://www.researchgate.net/publication/371985656

[32] F. Faul, A. Buchner, E. Erdfelder, and S. Mayr, "A short tutorial of GPower," *Tutor. Quant. Methods Psychol.*, vol. 3, no. 2, 2007.

[33] S. Mayr, E. Erdfelder, A. Buchner, and F. Faul, "A short tutorial of GPower," *Tutor. Quant. Methods Psychol.*, vol. 3, no. 2, 2007, doi: 10.20982/tqmp.03.2.p051.

[34] J. F. Hair, C. M. Ringle, S. P. Gudergan, A. Fischer, C. Nitzl, and C. Menictas, "Partial least squares structural equation modeling-based discrete choice modeling: an illustration in modeling retailer choice," *Bus. Res.*, vol. 12, no. 1, pp. 115–142, 2019, doi: 10.1007/s40685-018-0072-4.

[35] A. Bhandar, "Multicollinearity | Causes, Effects and Detection Using VIF (Updated 2023)," Analitycs Vidhya.

[36] J. Henseler, "Partial least squares path modeling: Quo vadis?," *Qual. Quant.*, vol. 52, no. 1, pp. 1–8, 2018, doi: 10.1007/s11135-018-0689-6.

[37] G. Shmueli *et al.*, "Predictive model assessment in PLS-SEM: guidelines for using PLSpredict," *Eur. J. Mark.*, vol. 53, no. 11, pp. 2322–2347, 2019, doi: 10.1108/EJM-02-2019-0189.

[38] J. F. Hair, J. J. Risher, M. Sarstedt, and C. M. Ringle, "When to Use and How to Report the Results of PLS-SEM," *Eur. Bus. Rev.*, vol. 31, no. 1, pp. 2–24, 2019, doi: 10.1108/EBR-11-2018-0203.

[39] M. Sarstedt, J. F. Hair, J. H. Cheah, J. M. Becker, and C. M. Ringle, "How to specify, estimate, and validate higher-order constructs in PLS-SEM," *Australas. Mark. J.*, vol. 27, no. 3, pp. 197–211, 2019, doi: 10.1016/j.ausmj.2019.05.003.

[40] J. Henseler, C. M. Ringle, and M. Sarstedt, "A new criterion for assessing discriminant validity in variance-based structural equation modeling," *J. Acad. Mark. Sci.*, vol. 43, no. 1, 2015, doi: 10.1007/s11747-014-0403-8.

[41] M. Sarstedt, J. F. Hair, C. Nitzl, C. M. Ringle, and M. C. Howard, "Beyond a tandem analysis of SEM and PROCESS: Use of PLS-SEM for mediation analyses!," *Int. J. Mark. Res.*, vol. 62, no. 3, pp. 288–299, 2020, doi: 10.1177/1470785320915686.

[42] W. W. Chin, "The partial least squares approach to structural equation modelling. In Marcoulides G. A. (Ed.)," in *Modern Methods for Business Research*, vol. 295, no. 2, 1998.

[43] G. Dash and J. Paul, "CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting," *Technol. Forecast. Soc. Change*, vol. 173, no. July, p. 121092, 2021, doi: 10.1016/j.techfore.2021.121092.

[44] J. Cohen, *Statistical power analysis for the behavioral sciences (2nd ed.)*, Second. Hillsdale, NJ: Erlbaum., 1988. doi: https://doi.org/10.4324/9780203771587.

## BIOGRAPHIES OF AUTHORS

| | |
|---|---|
|  | **Hildawati, Ph. D (Cand)** Lecturer at the STIA Lancang Kuning Dumai in Riau, Indonesia. She earned her Bachelor's degree in Social Administration from Universitas Riau in 2005. In 2012, she obtained her Master's degree in Public Administration with a concentration in Public Policy from Universitas Islam Riau. Currently, she is pursuing her Ph.D. at Universiti Utara Malaysia in the School of Government. Her research focuses on the use of technology in governance. She has produced several academic manuscripts to support policy formulation in the Dumai City Government.She is also actively engaged in writing books and has obtained twelve national copyrights from the Ministry of Law and Human Rights of Indonesia for her works. She can be contacted via email at hildrias81@gmail.com or hildawati_h@uum.edu.my. |
| | |
|  | **Dedy Afrizal, S.Sos., M.Si., Ph.D** Bachelor's degree Public Administration from STIA Lancang Kuning Dumai, Master's degree in Public Administration and Public Policy from the University of Riau, and Philosophy of Doctoral Program (Public Administration) at Universiti Utara Malaysia. A researcher and lecturer in the Public Administration Study Program at the Faculty of Social and Political Sciences, Raja Ali Haji Maritime University (UMRAH), Tanjung Pinang, Indonesia. Focused in research within the domain of E-Government ICT in the Public Sector, Public Service, Local Authorities, and the Digital Divide. Email: dedyafrizal@umrah.ac.id |
| | |
|  | **Lis Hafrida** Lecturer at Universitas Dumai, Indonesia. She received her Bachelor's degree in Education from Universitas Bung Hatta in 1994 and her Master's degree in Environmental Science from Universitas Riau in 2009. Her research interests focus on technology education and the social sciences. She is actively involved in teaching and academic activities related to the development of science and education. She can be contacted at lis.hafrida@gmail.com |
| | |
|  | **Dina Purnamasari, S.IP., M. AP** Bachelor's degree International Relations from University of Riau, and Master's degree in Public Administration from the University of Riau. A researcher and lecturer in the Governmental Science Study Program at the Faculty of Social and Political Sciences, Raja Ali Haji Maritime University (UMRAH), Tanjung Pinang, Indonesia. Focused in research within the domain of public service management, collaborative governance, and human resource management. Email: dinapurnamasari@umrah.ac.id |
| | |
|  | **Ahmad Luthfi, S.Sos., M.A.P.** Bachelor's degree Public Administration from the University of Hasanuddin, Master's degree in Public Administration from the University of Hasanuddin. A researcher and lecturer in the Public Administration Study Program at the Faculty of Social and Political Sciences, University of Merdeka Malang, Indonesia. Focused in research within the domain of E-Government, Public Service, Bureaucracy, Collaborative Governance, Governance and Governance Innovation. Email: ahmad.luthfi@unmer.ac.id |
| | |