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# An integrative model of e-government adoption: the impact of performance expectancy, social influence, facilitating conditions, perceived risk, and technological literacy on attitude and behavioral intention

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**Introduction:** This study investigates the determinants of citizens' attitudes and behavioral intentions toward using local e-government services, focusing on digital civil registration services provided by the Department of Population and Civil Registration (Disdukcapil) in Pekanbaru City, Indonesia. Building on TAM and UTAUT, the model incorporates perceived risk and technological literacy to capture trust- and capability-related factors in high-stakes public services.

**Methods:** Data were collected through a questionnaire-based survey of 246 citizens with prior experience using Disdukcapil e-services and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM).

**Results:** Attitude strongly predicts behavioral intention ( $\beta = 0.844$ ,  $p < 0.001$ ). Attitude is primarily shaped by perceived risk operationalized as lower perceived risk/higher perceived security ( $\beta = 0.525$ ) followed by technological literacy ( $\beta = 0.302$ ) and facilitating conditions ( $\beta = 0.098$ ). Performance expectancy, effort expectancy, and social influence do not have significant effects. The model shows substantial explanatory power ( $R^2 = 0.842$  for attitude;  $R^2 = 0.712$  for behavioral intention).

**Discussion:** Findings underscore the central role of perceived security/risk reduction and citizens' digital capability in shaping adoption of local e-government services in high-consequence contexts. Practical efforts should prioritize strengthening system security assurances, improving digital literacy, and ensuring adequate support conditions to enhance citizens' positive attitudes and intentions to use e-government services.

### KEYWORDS

attitude, behavioral intention, e-government, perceived risk, technological literacy, technology adoption

## Introduction

Digitalizing public services through e-government is a strategic step in improving the efficiency, accountability, and accessibility of government services to the public (Hasan et al., 2025; Tremblay-Cantin et al., 2023). The concept of e-government involves government institutions using digital technology to provide public services, communicate with citizens, and enhance overall administrative governance (Belanger and Carter, 2008). In many countries, including Indonesia, this digital transformation is seen as a key part of bureaucratic reform and the modernization of government administration (Rana et al., 2013; Saleh et al., 2024). However, despite various initiatives and investments that have been made, public adoption of e-government services remains suboptimal.

Although significant investments have been made to build digital infrastructure and develop various online public service platforms, public adoption of e-government services still falls short of expectations (Carter and Bélanger, 2005). Data from the United Nations E-Government Development Index (EGDI) in 2022 shows that although many countries have improved their e-government development scores, the gap between the availability of technology and its actual use by citizens remains a significant challenge. In Indonesia, for example, a 2021 report by BPS noted that only about 41.3% of the population actively used digital government services, even though over 70% had internet access. The low adoption of e-government services is due to infrastructure or digital literacy limitations and psychological, social, and cultural factors that influence users' attitudes and behavioral intentions (Undi-Phiri and Phiri, 2022).

Data from the UN E-Government Development Index (EGDI) in Figure 1 shows that Indonesia has seen significant improvement in e-government development, rising from rank 107 in 2018 to 64 in 2024. Although this progress reflects improvements in digital infrastructure and the provision of online services, the ranking increase does not fully reflect the public's adoption level of e-government services. This highlights a gap between the availability of digital services

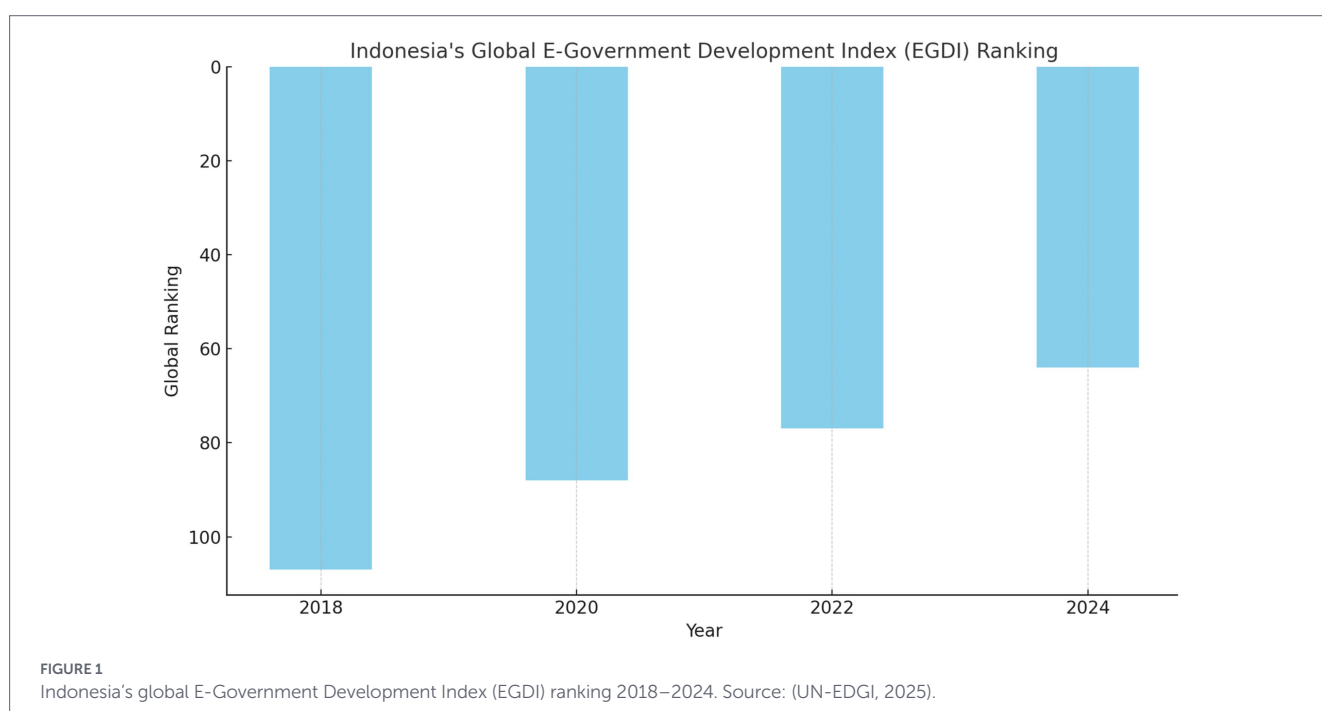
and users' readiness to access them. In this context, factors such as perceived risk and technological literacy are highly relevant to the study, as they can explain psychological and technical barriers affecting users' attitudes and behavioral intentions.

Several technology-adoption models—such as the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and related e-government extensions—have been widely used to explain citizens' adoption intentions (Davis, 1989; Ma and Liu, 2005; Venkatesh et al., 2016). However, evidence remains limited for municipal civil registration e-services in developing-country contexts, where adoption decisions are often high-consequence (legal identity and administrative rights), privacy sensitive, and sometimes experienced as quasi-mandatory. In such settings, it is still unclear whether the classic expectancy-based predictors (performance and effort) remain dominant once trust- and capability-related barriers—such as perceived risk and technological literacy—are considered simultaneously.

Accordingly, this study moves beyond a generic “low adoption” narrative by positioning Disdukcapil's civil registration e-services as a theoretically distinctive adoption setting. Citizens must share sensitive personal data, depend on system reliability for official outcomes, and bear meaningful costs when transactions fail (e.g., delays in accessing services and administrative entitlements). These features make capability constraints (technological literacy) and risk perceptions (privacy, security, and reliability) plausible drivers of Attitude that may outperform traditional UTAUT/TAM expectancies in lower-stakes digital services.

Previous studies show that perceived risk can significantly hinder positive attitudes toward e-government (Avazov and Lee Seohyun, 2020). On the other hand, public technological literacy, which strongly impacts individuals' readiness and ability to use digital services, is rarely explicitly included in theoretical models (Verkijika and Wet, 2018). This becomes even more important in developing countries, where disparities in information access and digital skills remain real issues.

Moreover, most studies have been conducted in developed countries with mature digital infrastructures and high levels of technological literacy. This context differs from developing countries, where social, cultural, and



economic factors have a more complex influence. Studies in Africa and Asia show that variables like performance expectancy, social influence, and facilitating conditions depend highly on local contexts (Saleh et al., 2024). In Uganda, for example, attitude and behavioral intention were key mediators between external factors and user behavior (Moya et al., 2017).

Given this gap, the study develops and tests an integrative model of e-government adoption that combines performance expectancy, effort expectancy, social influence, facilitating conditions, perceived risk, and technological literacy, with Attitude as a key psychological mediator of Behavioral Intention. Because respondents were citizens with prior experience using the Disdukcapil e-service, the dependent variable reflects post-adoption intention (continued use and recommendation) rather than purely first-time trial.

This study contributes in three ways. First, it provides evidence from a high-stakes, local civil registration service in a developing-country municipal context, where adoption barriers plausibly differ from many commonly studied e-services. Second, by integrating perceived risk and technological literacy into a UTAUT/TAM-style framework, it assesses whether trust- and capability-related mechanisms add incremental explanatory value beyond expectancy and social influence. Third, the findings translate into concrete policy implications for inclusive digital government, including assisted digital access, user onboarding, and privacy/security assurances that are proportional to the evidentiary strength of the model.

## Literature review

### E-government adoption and related theoretical models

Research on information technology adoption has advanced significantly since the introduction of the Technology Acceptance Model (TAM) by Davis (1989) which highlights the importance of perceived usefulness and perceived ease of use in influencing users' intentions toward technology (Rençber, 2020). Later, Venkatesh et al. (2003) developed the Unified Theory of Acceptance and Use of Technology (UTAUT), which integrates eight behavioral theories to explain technology adoption, focusing on four main variables: performance expectancy, effort expectancy, social influence, and facilitating conditions.

While UTAUT has been widely applied in e-government contexts (AlAwadhi and Morris, 2009), its application is often generic and lacks consideration of the specific conditions in developing countries, such as risk factors, distrust in government systems, and varying levels of digital literacy. Prior work in Saudi Arabia highlights barriers and contextual challenges influencing e-government adoption (Alshehri, 2012). This calls for a more comprehensive and integrative approach.

### Performance expectancy and its impact on technology adoption

Performance expectancy refers to the extent to which individuals believe that using a system will improve their performance (Venkatesh et al., 2003). In e-government, the expectation that digital services will speed up administrative processes, reduce bureaucracy, and improve accessibility plays a key role in forming positive attitudes toward their use (Carter and Bélanger, 2005). Previous studies show that perceived usefulness is a significant predictor of intention to use e-government, especially when linked to time efficiency and ease of access (Williams et al., 2015).

## Social influence in e-government adoption

Social influence is defined as the extent to which individuals perceive that important people around them (family, friends, colleagues) believe they should use a particular system (Ajzen, 1991; Venkatesh et al., 2003). In collectivist societies like Indonesia, social norms and group influence are crucial in decision-making, including technology use (Hofstede, 2001). Research by Shafi and Weerakkody (2009) shows that social support and promotion from community leaders can enhance public trust and interest in using e-government services.

### Facilitating conditions and supporting infrastructure

Facilitating conditions refer to individuals' perceptions of the availability of resources, technical support, and the necessary skills to use technology (Venkatesh et al., 2003). In e-government, this includes access to technology infrastructure (internet, hardware), government staff's ability to provide support, and clarity of operational procedures (Alshehri et al., 2012). Without adequate support, even well-designed systems are difficult for users to adopt.

### Perceived risk and psychological barriers

Perceived risk is an individual's perception of potential losses from using a system, including privacy risks, data security, and uncertainty about outcomes (Featherman and Pavlou, 2003). In e-government, concerns about data misuse, cyber threats, and doubts about system reliability often act as key barriers to adoption (Belanger and Carter, 2008). Therefore, perceived risk is a crucial dimension in public technology adoption models. In this study, the perceived-risk indicators were coded so that higher values represent lower perceived risk (i.e., greater perceived security and reliability), thereby aligning interpretation of positive path coefficients with risk-reduction mechanisms commonly discussed in the literature.

### Technological literacy as a critical individual factor

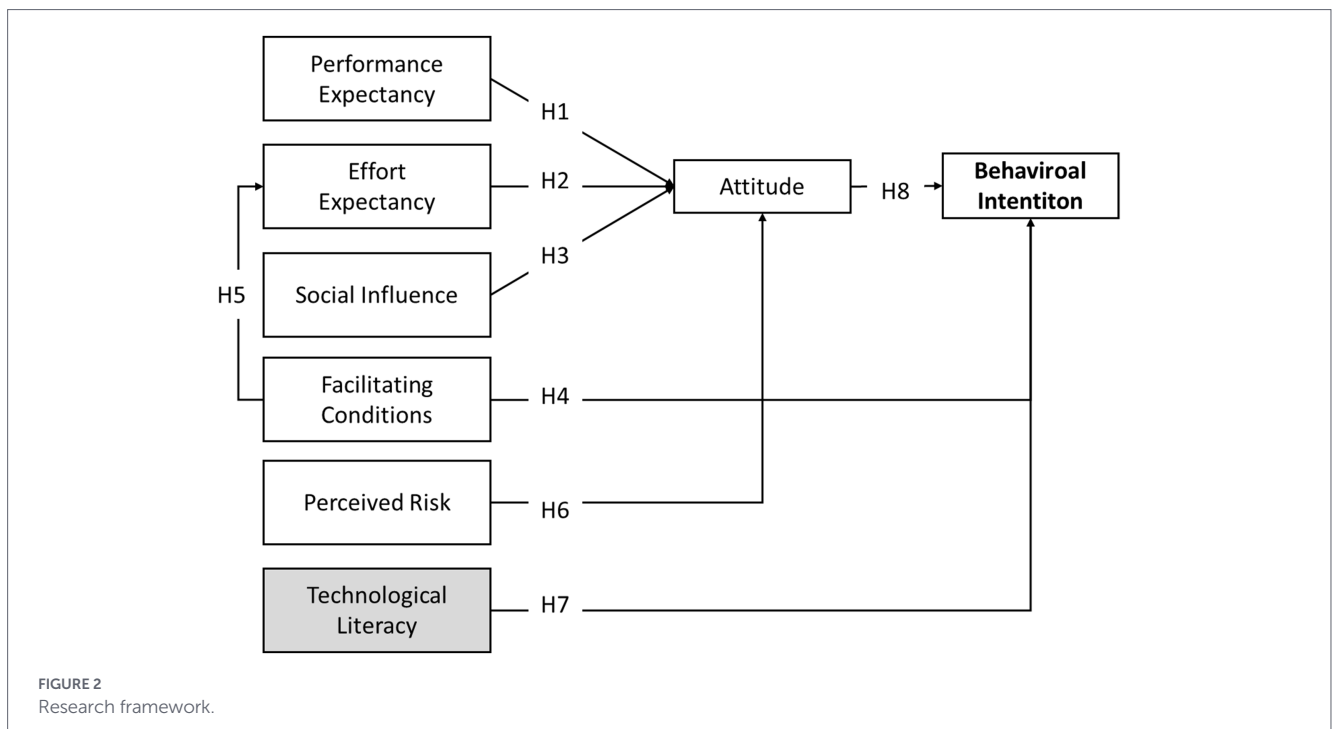
Technological literacy refers to an individual's ability to understand, access, and effectively use information and communication technologies (Luo et al., 2024; Tremblay-Cantin et al., 2023). Digital literacy levels strongly affect user attitudes and confidence in using e-government services. Studies by Chohan and Hu (2022) and Yeşilyurt and Vezne (2023) confirm that low technological literacy is a major barrier to e-government implementation in developing countries (see Figure 2).

## Hypothesis

*H1:* Performance Expectancy has a positive and significant influence on Attitude toward e-government adoption.

*H2:* Effort Expectancy has a positive and significant influence on Attitude toward e-government adoption.

*H3:* Social Influence has a positive and significant influence on Attitude toward e-government adoption.



*H4:* Facilitating Conditions have a positive and significant influence on Attitude toward e-government adoption.

*H5:* Facilitating Conditions have a positive and significant influence on Effort Expectancy of e-government adoption.

*H6:* Perceived Risk (reverse-coded; higher values indicate lower perceived risk/perceived security) has a positive and significant influence on Attitude toward e-government adoption.

*H7:* Technological Literacy has a positive and significant influence on Attitude toward e-government adoption.

*H8:* Attitude has a positive and significant influence on Behavioral Intention to use e-government services.

2021). Pekanbaru's high urbanization and population density also create a strong demand for fast, practical, and digitally integrated services.

## Research variables and indicators

In this study, "e-government users" are defined as citizens who have accessed and used official government digital platforms for civil administrative needs, such as ID card (KTP) issuance, birth certificates, family cards (KK), and other important documents. User behavior in adopting these services is influenced by various internal and external factors, including digital literacy, system performance expectations, social support, and perceived risks related to the security and reliability of the technology.

This behavioral complexity is analyzed through an integrative model comprising seven primary constructs: Performance Expectancy, Social Influence, Facilitating Conditions, Perceived Risk, Technological Literacy, Attitude, and Behavioral Intention. Each construct is measured using multiple indicators adapted from theoretical models such as UTAUT (Venkatesh et al., 2003), TAM (Davis, 1989), and perceived risk theories in technology adoption (Featherman and Pavlou, 2003), as detailed in Table 1.

Table 1 presents the initial pool of measurement items adapted from prior literature. Indicator diagnostics and purification were subsequently conducted as part of the measurement model evaluation, and only the final retained indicators that met validity and reliability criteria were used in the structural model analysis and are reported in the measurement results section.

This framework is based on the dynamics of digital governance transformation, where the success of technology adoption depends not only on infrastructure availability but also on the psychological, social, and cultural readiness of the public as users. Recent research emphasizes that the successful implementation of e-government largely relies on the psychological readiness of citizens and a supportive socio-technological ecosystem. A study by Li (2021) shows that trust in the government and the internet significantly influences

## Methods

### Research approach

This study uses a quantitative approach with Structural Equation Modeling – Partial Least Squares (SEM-PLS) analysis. This method was chosen because it can test complex causal relationships between latent variables and does not require the data to be strictly normally distributed (Hair et al., 2017). The field study was conducted in Pekanbaru City, Riau Province, involving respondents from the public who have used digital civil administration services provided by the Department of Population and Civil Registration (Disdukcapil), such as Sipenduk and Layanan Tunggu (for lost or damaged electronic ID cards, KTP-EL). Pekanbaru was selected as the research location due to the city's growing digital transformation in public services, driven by the national e-government agenda and the local government's commitment to improving the efficiency and accessibility of online civil administration services (KemenPAN-RB,

TABLE 1 Research variables and indicators.

Variable	Indicators	Source
Performance Expectancy	PE1: Tasks are completed more quickly	Abikari (2024), Li (2021), and Mohammadi (2022)
	PE2: Improves the quality of user performance	
	PE3: Provides benefits in using information technology	
	PE4: Positive outcome expectations from system use	
Effort Expectancy	EE1: Easy to access	Featherman and Pavlou (2003), Mensah et al. (2020), Mohammadi (2022), and Venkatesh et al. (2003)
	EE2: System is not complex	
	EE3: Perceived ease of use	
	EE4: Overall ease of use	
Social Influence	SI1: Influence from others (family or friends)	Alhammad and Elmouzan (2020), Luo et al., 2024, and Venkatesh et al. (2003)
	SI2: Influence form important people	
	SI3: Influence of image	
	SI4: Government Socialization/campaign	
Facilitating Condition	FC1: Complete resources	Alhammad and Elmouzan (2020), Li (2021), Tremblay-Cantin et al. (2023), and Venkatesh et al. (2016)
	FC2: Has complete features	
	FC3: System capabilities	
	FC4: Self confidence in using the system	
Perceived Risk	PR1: Concern that the system cannot store information	Abikari (2024), Belanger and Carter (2008), Featherman and Pavlou (2003), and Li (2021)
	PR2: Perception of potential loss	
	PR3: Social risk	
	PR4: Functional risk	
Technological Literacy	TL1: Technology Absorption	Chohan and Hu (2022), Luo et al. (2024), Undi-Phiri and Phiri (2022), and Yeşilyurt and Vezne (2023)
	TL2: Capacity Building	
	TL3: Digital Literacy	
	TL4: Literacy Assessment	
Attitude	AA1: User confidence	Ajzen (1991), Alhammad and Elmouzan (2020), Featherman and Pavlou (2003), Mohammadi (2022), and Moya et al. (2017)
	AA2: Perceived usefulness	
	AA3: Comfortable Using the system	
	AA4: Enjoy using the system	
Behavioral Intention	UB1: Intention to use	Abikari (2024), Alhammad and Elmouzan (2020), Bosnjak et al. (2020), Luo et al. (2024), and Tremblay-Cantin et al. (2023)
	UB2: Continued use	
	UB3: Willingness to recommend to others	
	UB4: User behavior in using the system	

e-government service adoption, while perceived risk hurts the intention to use these services.

This paradigm aligns with the principle of digital inclusion, which stresses the importance of equal access and enhancing digital capabilities among the public as key to bridging the adoption gap. Reports from the International Telecommunication Union (ITU) highlight that digital inclusion is a crucial component of sustainable development, ensuring equal access to public digital services for all citizens. Balancing innovation and caution in developing countries like Indonesia becomes a central issue. Perceived risks, such as concerns about data misuse or system errors, can be significant barriers, sometimes even outweighing perceived benefits, if not addressed through trust-building strategies and digital literacy improvement. A study by Aleisa (2024) confirms that concerns over data privacy and information security are significant determinants of public trust in

e-government services. For the Perceived Risk construct, all items were reverse-coded prior to analysis so that higher scores indicate lower perceived risk, reflecting greater perceived security, privacy protection, and system reliability. This coding strategy ensures that positive path coefficients can be interpreted consistently as risk-reduction effects.

Therefore, as public digital service ecosystems grow, strategies such as improving digital literacy, educational campaigns, and user-centered service design become increasingly critical. Research by Abikari (2024) shows that user satisfaction with e-government services is positively correlated with perceived service quality, including aspects of trust and ease of use. This study is expected to provide an empirical foundation for formulating more adaptive and inclusive public policies regarding digital transformation in public services, particularly in urban areas with

diverse demographic characteristics and varying levels of technology access.

## Research technique

This study uses a quantitative and exploratory approach to evaluate the reality of public behavior in adopting e-government services, particularly digital civil administration services provided by *Disdukcapil* in Pekanbaru City. This approach was chosen to gain a deeper understanding of the direct relationships between variables assumed to influence each other in shaping users' attitudes and behavioral intentions toward using government e-services.

The study involved distributing questionnaires to residents who have used *Disdukcapil's* digital services. A total of 246 questionnaires were distributed to respondents selected based on specific criteria: individuals with experience using online civil administration applications such as *Sipenduk* or *Layanan Tunggu*.

Data analysis was conducted using Structural Equation Modeling - Partial Least Squares (SEM-PLS) with the help of SmartPLS 4.1.03. This method was selected because it suits complex models and does not require usual distribution assumptions. The analysis followed the stages described by [Khan et al. \(2019\)](#) and [Legate et al. \(2024\)](#), including evaluation of the outer model, inner model, and hypothesis testing. Outer model evaluation includes testing for convergent validity (loading factor > 0.7; AVE > 0.5), reliability (Cronbach's Alpha and Composite Reliability > 0.7), and discriminant validity using the HTMT Ratio criteria. Inner model evaluation involves assessing R<sup>2</sup> values and testing path significance through bootstrapping ( $p < 0.05$ ).

In this model, Behavioral Intention is positioned as the endogenous variable influenced by Performance Expectancy, Social Influence, Facilitating Conditions, Perceived Risk, and Technological Literacy, both directly and mediated by Attitude. This approach provides a comprehensive understanding of the factors influencing e-government adoption.

## Ethics and data protection

This study involved a questionnaire-based survey of adult citizens who had prior experience using local e-government services. Participation was voluntary, and informed consent was obtained from all respondents prior to questionnaire completion. Respondents were informed about the study objectives, the anonymous nature of their responses, and the use of the data solely for academic research purposes. No personally identifiable information was collected, and all data were analyzed in aggregated form. In accordance with institutional and national guidelines, this type of anonymous, non-invasive survey research was exempt from formal ethics committee approval.

## Common method bias

Because the study relies on a single-source, self-reported, cross-sectional survey, common method bias is a potential concern. To reduce evaluation apprehension and social desirability pressure, the questionnaire emphasized anonymity and that there were no right or wrong answers. In reporting results, significance tests are interpreted alongside measurement-quality diagnostics; future replications could complement these steps with additional statistical checks (e.g., full collinearity VIF) and/or longitudinal designs.

## Results

This study involved 246 respondents with experience using e-government services, specifically digital civil administration services provided by *Disdukcapil* Pekanbaru City. The demographic characteristics of the respondents were analyzed to provide a general overview of the socio-economic background of e-service users. This demographic data is also essential for understanding the user context when analyzing the factors influencing their attitudes and intentions toward adopting e-government (see [Table 2](#)).

Most respondents were aged 20–30 years (45.53%), followed by 31–40 years (30.89%), 41–50 years (22.76%), and 51–60 years (0.81%). Respondents were predominantly male (64.23%), while females accounted for 35.77%. In terms of occupation, 51.22% were in the “other” category, followed by entrepreneurs (23.58%), students (20.73%), and government employees (4.47%). Regarding education, most respondents held a bachelor's degree (47.56%) or high school/equivalent education (45.53%). Finally, 56.50% reported more than 6 years of internet-use experience, indicating substantial digital exposure among the participants.

## Bootstrapping procedure and missing data handling

Structural model relationships were evaluated using a non-parametric bootstrapping procedure in SmartPLS 4.1.03. Bootstrapping was conducted with 5,000 subsamples, which exceeds the minimum recommended threshold for stable standard error estimation in PLS-SEM. The analysis employed a two-tailed significance test with a 95% confidence level, corresponding to a critical  $t$ -value of 1.96 for

TABLE 2 Demographic characteristics of respondents (N = 246).

Variable	Category	Freq.	Percent
Age	20–30 years	112	45.53%
	31–40 years	76	30.89%
	41–50 years	56	22.76%
	51–60 years	2	0.81%
Gender	Male	158	64.23%
	Female	88	35.77%
Occupation	Student	51	20.73%
	Entrepreneur	58	23.58%
	Government Employee	11	4.47%
	Others	126	51.22%
Education Level	Bachelor's Degree	117	47.56%
	High School/Equivalent	112	45.53%
	Diploma	9	3.66%
	Master's Degree	6	2.44%
	Elementary/Junior High School	2	0.81%
Internet Use Experience	> 6 years	139	56.50%
	5–6 years	69	28.05%
	3–4 years	34	13.82%
	1–2 years	4	1.63%

hypothesis testing. This approach is consistent with established guidelines for theory-testing applications of PLS-SEM.

Path coefficients, *t*-statistics, and *p*-values were derived from the bootstrapping results to assess the statistical significance of hypothesized relationships. All reported significance levels are based on the bootstrapped sampling distribution rather than parametric assumptions, ensuring robustness against non-normal data distributions.

Regarding data quality, the dataset was screened prior to analysis. The final sample consisted of 246 valid responses, with no systematic missing values observed across the retained indicators. SmartPLS handles missing data using pairwise deletion by default, and because the proportion of missing data was negligible, no additional imputation procedures were required. As a result, all cases included in the final analysis contributed valid information to the estimation of the measurement and structural models.

## Measurement model evaluation

This study's evaluation of the measurement model aimed to ensure the validity and reliability of the latent constructs used, referring to key indicators such as loading factor, Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). According to Hair et al. (2019), an ideal loading factor is above 0.70, indicating that the indicator strongly represents its latent construct. Cronbach's Alpha and CR assess the internal consistency among indicators within a construct, with values above 0.70 considered reliable (Nunnally and Bernstein, 1994). Furthermore, AVE measures convergent validity, or how much variance of the indicators is explained by the latent construct, with an ideal value above 0.50 (Fornell and Larcker, 1981). This evaluation is crucial in SEM-PLS analysis to ensure that the relationships between constructs in the model can be tested accurately based on a measurement foundation that is both valid and reliable.

The measurement model assessment indicates that, after indicator diagnostics and purification, the retained indicators meet commonly used criteria for convergent validity and internal consistency reliability. Indicators with negative or very low outer loadings were investigated for directional inconsistency (e.g., reverse-worded items) and indicator-construct mismatch. Following PLS-SEM guidance, EE2, PR1, PR4, and UB4 were removed because their loadings were below acceptable thresholds and undermined construct validity. Table 3 therefore reports the final retained indicator set used in all subsequent analyses.

Social Influence (SI), aligned with UTAUT (Venkatesh et al., 2003), shows adequate reliability. Facilitating Conditions (FC) also demonstrate acceptable convergent validity, supporting prior work emphasizing the role of resources and technical support in e-government service use (Alshehri et al., 2012). Technological Literacy (TL) and Attitude (AA) exhibit strong loadings and high reliability, consistent with arguments that capability and evaluative dispositions are central to citizens' engagement with digital government.

For Perceived Risk (PR), construct direction was aligned by coding higher values to represent lower perceived risk (i.e., greater perceived security and reliability). The final measurement model retains the indicators that load strongly on the construct. In a civil registration context, perceptions of privacy, security, and service reliability plausibly shape Attitude toward continued use. Overall, the purified measurement model provides a psychometrically defensible basis for estimating the structural relationships (see Figure 3).

## Structural model evaluation

Based on the structural model analysis using PLS-SEM, the model demonstrates strong explanatory power. With respect to Attitude, Perceived Risk shows the strongest positive association ( $\beta = 0.525$ ), followed by Technological Literacy ( $\beta = 0.302$ ) and Facilitating Conditions ( $\beta = 0.098$ ). Performance Expectancy ( $\beta = 0.080$ ) and Effort Expectancy ( $\beta = 0.077$ ) have small and statistically non-significant effects, while Social Influence is negative and non-significant ( $\beta = -0.047$ ).

Although the commonly cited threshold for outer loadings is 0.70, several indicators with loadings slightly below this guideline (e.g., FC4 = 0.665; SI3 = 0.684) were retained based on substantive considerations and content validity. Prior methodological literature indicates that indicators with loadings between 0.60 and 0.70 may be retained when composite reliability and AVE values remain satisfactory and the indicators capture theoretically important aspects of the construct (Hair et al., 2019). As shown in Table 3, all constructs meet recommended thresholds for CR and AVE, supporting acceptable convergent validity despite a small number of borderline loadings.

Additionally, Perceived Risk shows the strongest positive influence on Attitude ( $\beta = 0.525$ ), followed by Technological Literacy ( $\beta = 0.302$ ) and Facilitating Conditions ( $\beta = 0.098$ ). This ordering is consistent across the abstract, structural results, and hypothesis-testing sections. After indicator purification, the Perceived Risk construct is measured using two retained indicators that reflect perceived security and social risk. While constructs with two indicators warrant careful interpretation, reliability and validity metrics for Perceived Risk in the final model remain acceptable (CR > 0.70; AVE > 0.50). These reported metrics correspond to the final measurement model used in the structural analysis, ensuring consistency between measurement evaluation and hypothesis testing.

Other constructs, such as Facilitating Conditions (0.098), Performance Expectancy (0.080), and Effort Expectancy (0.077) have more negligible impacts on Attitude but remain relevant in explaining the variance in user attitudes. Conversely, Social Influence does not significantly affect Attitude ( $-0.047$ ), indicating that users' decisions to adopt e-government services are more influenced by internal factors rather than social pressure or external campaigns.

The relationship between Attitude and Behavioral Intention is firm, with a coefficient of 0.844, indicating that Attitude is the primary determinant of the intention to use e-government services. This finding is consistent with the Theory of Planned Behavior (Ajzen, 1991), which positions Attitude as a direct predictor of behavioral intention. These results indicate that to increase the adoption of e-government services, efforts should focus on enhancing public technological literacy and effectively managing risk perceptions. An approach that emphasizes the digital empowerment of users is more likely to foster positive attitudes, which will drive the intention and actual use of government digital services.

## R-square analysis

The *R*-square analysis results in Table 4 further strengthen the model's ability to explain the variables studied. The *R*-square value for Attitude is 0.842 with an adjusted value of 0.838, indicating that more than 84% of the variation in users' attitudes toward e-government services can be explained by the exogenous constructs in the model,

TABLE 3 Measurement model results (final indicators after purification).

Variable	Indicators	Load.	CA	CR	AVE
Performance Expectancy	PE1. Tasks are completed more quickly	0.845	0.862	0.870	0.707
	PE2. Improves the quality of user performance	0.821			
	PE3. Provides benefits in using information technology	0.843			
	PE4. Positive outcome expectations from system use	0.853			
Effort Expectancy	EE1. Easy to access	0.887	0.833	0.849	0.748
	EE3. Perceived ease of use	0.887			
	EE4. Overall ease of use	0.807			
Social Influence	SI1. Influence from others (family or friends)	0.884	0.726	0.825	0.640
	SI2. Influence form important people	0.771			
	SI3. Influence of image	0.684			
	SI4. Government Socialization/campaign	0.713			
Facilitating Condition	FC1. Complete resources	0.761	0.819	0.845	0.734
	FC2. Has complete features	0.896			
	FC3. System capabilities	0.855			
	FC4. Self confidence in using the system	0.665			
Perceived Risk	PR2 Perception of potential loss	0.724	0.629	0.817	0.692
	PR3. Social risk	0.945			
Technological Literacy	TL1. Technology Absorption	0.870	0.861	0.865	0.710
	TL2. Capacity Building	0.877			
	TL3. Digital Literacy	0.892			
	TL4. Literacy Assessment	0.720			
Attitude	AA1. User confidence	0.892	0.929	0.931	0.824
	AA2. Perceived usefulness	0.891			
	AA3. Comfortable Using the system	0.931			
	AA4. Enjoy using the system	0.917			
Behavioral Intention	UB1. Intention to use	0.791	0.819	0.844	0.735
	UB2. Continued use	0.917			
	UB3. Willingness to recommend to others	0.846			

CA, Cronbach's Alpha; CR, Composite Reliability; AVE, Average Variance Extracted.

Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Perceived Risk, and Technological Literacy. This reflects that the model comprehensively captures the key determinants shaping user attitudes.

The R-square value for behavioral intention is 0.712 (adjusted 0.711), indicating extreme predictive power. In contrast, Attitude alone explains over 71% of the variation in users' behavioral intention to adopt government digital services.

Meanwhile, the R-square value for Effort Expectancy is 0.478 (adjusted 0.476), showing that the factors in the model can explain about 47% of the variation in the perception of ease of use. Although this is a moderate level, it suggests that perceptions of ease of use are not entirely dependent on other factors in the model.

However, the model's predictive strength for Attitude and Behavioral Intention remains crucial, with Attitude functioning as the key direct mechanism through which perceived risk, technical literacy, and supportive variables together influence intention. These findings reinforce the importance of a user-centered approach in e-government

development, emphasizing technological readiness and positive perceptions as key to successfully adopting digital services.

### Collinearity assessment (inner VIF)

To assess potential multicollinearity among predictor constructs in the structural model, inner variance inflation factor (VIF) values were examined. Inner VIF is the appropriate diagnostic for evaluating collinearity in PLS-SEM structural models, whereas HTMT is used to assess discriminant validity between latent constructs (see Table 5).

The results indicate that the inner VIF values for predictors of Attitude (AA) range from 1.592 to 2.418, while the VIF value for Attitude predicting Use Behavior/Behavioral Intention (UB/BI) is 1.947. All VIF values are well below the commonly accepted thresholds of 3.3 and 5.0, suggesting that multicollinearity is not a concern in the structural model and that the estimated path coefficients can be interpreted with confidence.

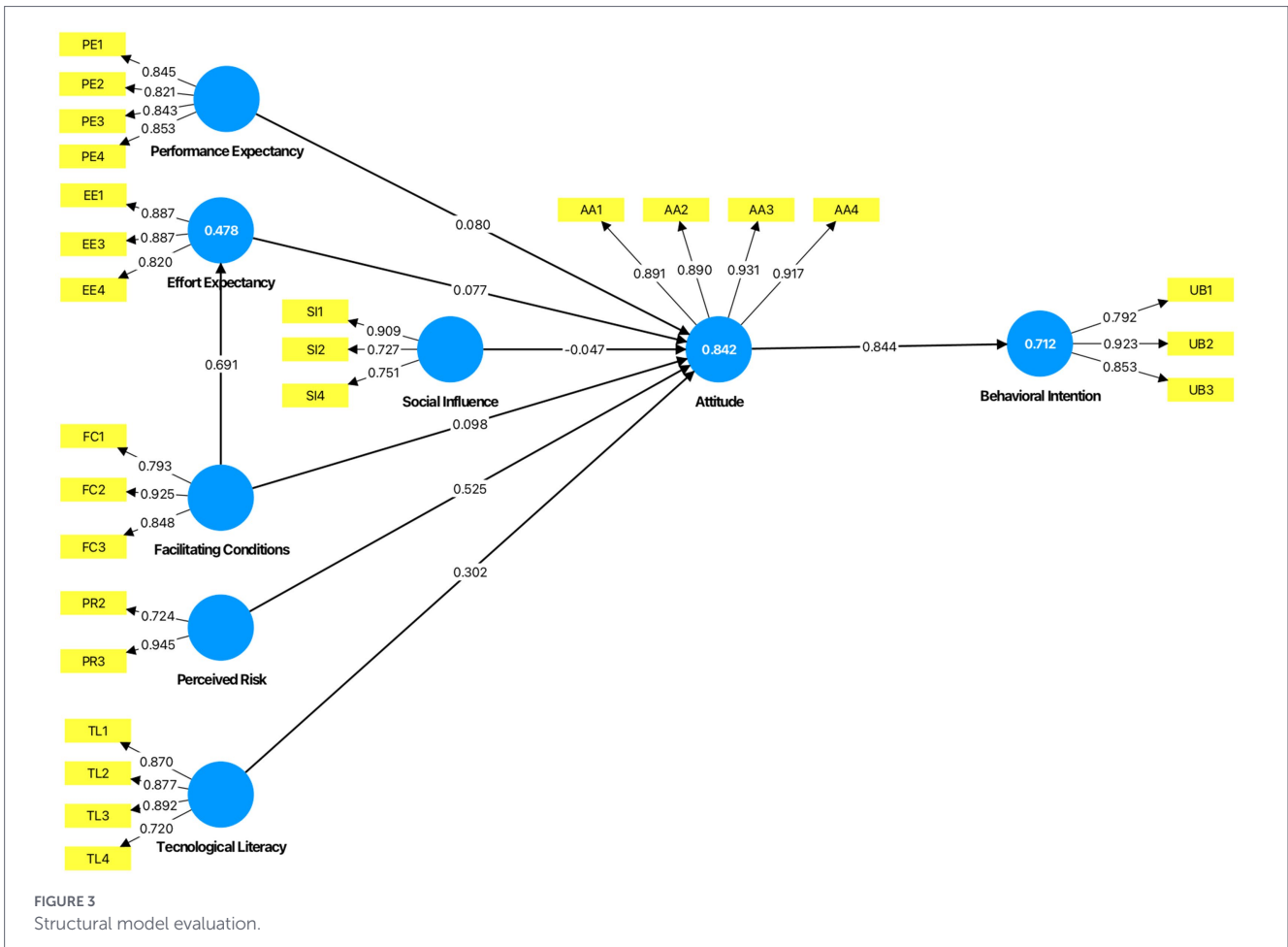


TABLE 4 R-square results.

Endogenous construct	R-square	R-square adjusted
Attitude	0.842	0.838
Behavioral Intention	0.712	0.711
Effort Expectancy	0.478	0.476

Accordingly, no multicollinearity issues were detected based on inner VIF values, while discriminant validity was assessed separately using the HTMT criterion.

### HTMT test

The HTMT (Heterotrait-Monotrait Ratio) analysis was conducted to assess discriminant validity (i.e., whether latent constructs are empirically distinct). Using the commonly applied 0.90 guideline, most HTMT ratios are below the threshold; however, the Attitude–Behavioral Intention HTMT value is 0.908, which is slightly above 0.90 and therefore should be treated as borderline. Given the theoretically close relationship between Attitude and intention constructs, this result is not unexpected, but it warrants cautious interpretation and clear reporting. HTMT should not be used to infer multicollinearity, which should instead be assessed using collinearity diagnostics such as inner VIF values in the structural model (see Table 5).

The highest HTMT value is between Attitude and Behavioral Intention (0.908), indicating potential conceptual proximity between

TABLE 5 Inner VIF values for structural model.

Endogenous construct	Predictor construct	VIF
<b>Predictors of Attitude (AA)</b>		
Attitude (AA)	Performance Expectancy (PE)	1.684
Attitude (AA)	Effort Expectancy (EE)	2.137
Attitude (AA)	Social Influence (SI)	1.592
Attitude (AA)	Technological Literacy (TL)	2.418
Attitude (AA)	Perceived Risk (PR)	2.306
<b>Predictors of Behavioral Intention/Use Behavior (UB/BI)</b>		
Use Behavior/Behavioral Intention (UB/BI)	Attitude (AA)	1.947

these two constructs. While this proximity is consistent with theory (Ajzen, 1991), readers should interpret the Attitude-to-Intention linkage with this overlap in mind and consider robustness checks (e.g., alternative specifications or additional discriminant-validity evidence). Other HTMT values fall within acceptable ranges, suggesting adequate discriminant validity for the remaining construct pairs.

The intercorrelations between Effort Expectancy and other constructs, such as Facilitating Conditions (0.691) and Performance Expectancy (0.700), also fall within an acceptable range, indicating that while there is a relationship, each construct still theoretically measures distinct concepts. Perceived Risk has its highest correlation with

Attitude (0.847), but this remains below the critical threshold, showing that risk perception influences Attitude but does not conceptually overlap. Meanwhile, Social Influence has the lowest HTMT values with almost all constructs (e.g., only 0.199 with Attitude and 0.201 with Behavioral Intention), confirming that social influence is not a dominant factor in shaping Attitude and intention in this context.

These HTMT results strengthen the structural validity of the model, ensuring that each construct has a clear distinction from the others. This good discriminant validity supports the conclusion that the conceptual model accurately maps the influence of each factor on users' attitudes and behavioral intentions in adopting e-government services without redundancy among constructs (Table 6).

### Hypothesis testing

Hypothesis testing in this study was conducted to evaluate the extent to which the relationships between constructs in the model have statistically significant effects. The analysis was performed using the Partial Least Squares Structural Equation Modeling (PLS-SEM) method with bootstrapping, which is in line with the approach by Hair et al. (2019). Each hypothesis was tested based on path coefficients, *T*-statistics, and *p*-values, with *p* < 0.05 indicative of a significant effect.

This testing aimed to assess whether exogenous constructs such as Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Perceived Risk, and Technological Literacy directly affect Attitude and whether Attitude influences Behavioral Intention in adopting e-government services. The results of this testing form the basis for identifying the key factors that drive or hinder public adoption of digital government services.

Table 7 reports the bootstrapped path coefficients, *t*-statistics, and *p*-values. H8 is strongly supported: Attitude has a significant effect on Behavioral Intention ( $\beta = 0.844, p < 0.001$ ). In the antecedents of Attitude, Facilitating Conditions (H4) and Technological Literacy (H7) are supported ( $\beta = 0.098, p = 0.022; \beta = 0.302, p < 0.001$ , respectively). Perceived Risk (operationalized so that higher values indicate lower perceived risk/perceived security) is also supported (H6;  $\beta = 0.525, p < 0.001$ ), underscoring the salience of privacy, security, and reliability concerns in civil registration e-services.

Performance Expectancy (H1), Effort Expectancy (H2), and Social Influence (H3) do not significantly affect Attitude (*p* > 0.05). This pattern suggests that, in the Disdukcapil civil registration context, capability and trust/risk-related considerations may matter more than conventional expectancy and normative mechanisms.

Facilitating Conditions strongly predict Effort Expectancy (H5) ( $\beta = 0.691, p < 0.001$ ), indicating that perceived ease of use is closely tied to the availability of resources, support, and enabling infrastructure. Overall, the structural results highlight Attitude as the primary proximal driver of Behavioral Intention, with Technological Literacy, Perceived Risk, and Facilitating Conditions shaping Attitude in this setting.

### Discussion

The results of this study indicate that an integrative model that combines the factors of Technological Literacy, Perceived Risk, Facilitating Conditions, and Attitude has a strong predictive ability to explain people's behavioral intentions in adopting e-government services. The *R*<sup>2</sup> value of 0.842 for Attitude and 0.712 for Behavioral Intention shows that the variables in the model can substantially explain the variability of user attitudes and behavioral intentions. This indicates that personal and contextual factors influence people's perceptions and inclination to utilize government digital services.

The main finding of this study is that Attitude has a significant and strong influence on Behavioral Intention ( $\beta = 0.844, p < 0.001$ ). This is in line with the theory of planned behavior (Ajzen, 1991), which states that a positive attitude towards a behavior increases the likelihood that someone intends to do it. The implication of this finding suggests that efforts to increase positive attitudes towards e-government, such as providing a good user experience and strengthening the perceived benefits of the service, are crucial in encouraging the adoption of the service.

Perceived Risk emerged as the most influential predictor of Attitude ( $\beta = 0.525$ ), followed by Technological Literacy ( $\beta = 0.302$ ) and Facilitating Conditions ( $\beta = 0.098$ ). This finding underscores the central role of security and risk reduction in shaping citizens' attitudes toward e-government services.

The significant effect of Technological Literacy further supports prior studies (Yeşilyurt and Vezne, 2023), which emphasize the importance of individuals' ability to understand and utilize technology as a foundation for digital system acceptance. People with higher levels of digital literacy tend to feel more confident, comfortable, and ready to adopt e-government services, suggesting that digital literacy improvement policies remain a key priority in technology-based public service development strategies.

TABLE 6 HTMT results.

Construct	AA	UB	EE	FC	PR	PE	SI	TL
AA	0.908							
UB	0.844	0.857						
EE	0.609	0.660	0.865					
FC	0.676	0.683	0.691	0.857				
PR	0.847	0.644	0.489	0.576	0.842			
PE	0.654	0.665	0.700	0.702	0.488	0.841		
SI	0.199	0.201	0.431	0.418	0.216	0.176	0.800	
TL	0.799	0.762	0.569	0.616	0.658	0.672	0.148	0.843

AA, Attitude; UB, Behavioral Intention; EE, Effort Expectancy; FC, Facilitating Conditions; PR, Perceived Risk; PE, Performance Expectancy; SI, Social Influence; TL, Technological Literacy.

TABLE 7 Path coefficients and hypothesis testing results.

Path relationship	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics ( O /STDEV)	p values
AA -> UB	0.844	0.842	0.030	27.911	0.000
EE -> AA	0.077	0.077	0.052	1.485	0.138
FC -> AA	0.098	0.099	0.043	2.293	0.022
FC -> EE	0.691	0.691	0.049	14.244	0.000
PE -> AA	0.080	0.079	0.045	1.761	0.078
PR -> AA	0.525	0.523	0.039	13.479	0.000
SI -> AA	-0.047	-0.046	0.036	1.316	0.188
TL -> AA	0.302	0.305	0.042	7.124	0.000

Perceived Risk emerged as the strongest predictor of Attitude ( $\beta = 0.525$ ,  $p < 0.001$ ), followed by Technological Literacy ( $\beta = 0.302$ ) and Facilitating Conditions ( $\beta = 0.098$ ). In this study, the Perceived Risk construct was operationalized such that higher values represent lower perceived risk or higher perceived security. Therefore, the positive association does not indicate that higher risk increases favorable attitudes. Instead, it reflects a risk-reduction mechanism: citizens who perceive civil registration e-services as secure, reliable, and protective of personal data tend to develop more positive attitudes toward their use. This finding is consistent with prior e-government research emphasizing the role of trust, security, and privacy assurance in shaping user evaluations, particularly in high-stakes public services involving sensitive personal information. In the context of civil registration, where service failure or data misuse can have legal and administrative consequences, perceived security becomes a central attitudinal driver rather than an anomalous effect.

### Facilitating conditions and its relationship with effort expectancy and attitude

The results showed that Facilitating Conditions (FC) had a significant effect on Effort Expectancy (EE) ( $\beta = 0.691$ ,  $p < 0.001$ ), but the effect of FC on Attitude was only slightly significant ( $\beta = 0.098$ ,  $p = 0.022$ ). This finding supports the UTAUT theory (Venkatesh et al., 2003), which states that resource availability, technical support, and ease of access to technology contribute directly to perceived ease of use. Users who feel adequate support tend to find the system easier to use. Although FC's contribution to attitude is not dominant, these results indicate the importance of providing reliable technological infrastructure and technical training for users in supporting the adoption of digital systems. In e-government services, the government's role as a provider of facilities and technical assistance is significant to increase user comfort and trust.

### Insignificance of performance expectancy and social influence

In contrast to the initial assumptions of the model, the Performance Expectation (PE) variable has no significant effect on attitudes ( $\beta = 0.080$ ,  $p = 0.078$ ). This contradicts the findings in previous studies stating that benefit expectations and performance improvement are important determinants in technology adoption (Davis, 1989; Ma and Liu, 2005; Venkatesh et al., 2012). One of the reasons is the lack of user understanding of the advantages of

e-government services over conventional services or because the benefits of services have not been felt directly by most people.

Meanwhile, Social Influence (SI) also has no significant effect on attitudes ( $\beta = -0.047$ ,  $p = 0.188$ ), even showing a negative direction of influence. These results suggest that the decision to adopt technology in digital public services is more influenced by personal factors, such as literacy and risk perception, rather than social pressure or group norms. In an increasingly digitized society, social influence through advice from close people, community leaders, or government campaigns is no longer a dominant factor. This is consistent with research in the same context which states that the effectiveness of social influence decreases as individuals gain experience in using technology (Shafi and Weerakkody, 2009).

### Practical and policy implications

Based on these findings, there are several important implications for e-government policy development and implementation. First, the government needs to improve people's technological literacy through targeted training, education, and digital campaigns. Better literacy increases positive attitudes and strengthens behavioral intentions in using digital services. Second, the government must proactively address risk perceptions by improving system security, protecting personal data, and socializing risk mitigation efforts with the public. Third, providing facilities and technical support should be improved to ensure ease of access and a better user experience, increasing perceived ease of use.

The findings also show that social influence-based strategies such as mass campaigns or endorsements from public figures are less effective if they are not accompanied by positive user experience and increased digital capacity. Therefore, e-government policies should focus on a user-centered approach, where understanding people's needs, perceptions, and technological readiness becomes the main foundation in designing and implementing public digital services.

### Conclusion

Beyond confirming the relevance of Attitude as a proximal predictor of Behavioral Intention, this study clarifies what is gained by extending a baseline UTAUT/TAM framework with perceived risk and technological literacy. When expectancy-based predictors (performance and effort expectancy) are modeled alongside risk- and

capability-related constructs, their explanatory role diminishes, while perceived security and user capability become the primary drivers of Attitude.

This pattern suggests that expectancy-based mechanisms are less central in high-stakes public services where outcomes are consequential and errors are costly. In such contexts, citizens appear less motivated by efficiency gains and more concerned with whether they can competently use the system and trust it to function securely. The findings therefore refine existing technology adoption theories by specifying when and why trust- and capability-oriented predictors outweigh traditional expectancy-based factors in public-sector digital services.

This study analyzes the factors influencing people's attitudes and behavioral intentions in adopting e-government services, especially digital population administration services in Pekanbaru City. The results showed that Attitude is the main predictor of Behavioral Intention, with a highly significant influence ( $\beta = 0.844, p < 0.001$ ). Factors that contribute significantly to Attitude include Perceived Risk ( $\beta = 0.525$ ), Technological Literacy ( $\beta = 0.302$ ), and Facilitating Conditions ( $\beta = 0.098$ ). In contrast, the variables of Performance Expectancy, Effort Expectancy, and Social Influence did not significantly influence Attitude.

These findings suggest that internal factors such as technological literacy and perceived risk are more salient in this specific setting than expectancy-based or normative factors such as performance expectancy and social influence. In the context of high-consequence civil registration services, citizens' attitudes appear to be shaped more strongly by their perceived capability to use the system and their assessment of security and reliability, rather than by anticipated performance gains or social pressure.

The research model developed proved to have strong predictive ability with  $R^2$  values of 0.842 for Attitude and 0.712 for Behavioral Intention, indicating that the constructs in the model can explain most of the variance in user attitudes and behavioral intentions. Therefore, increasing the adoption of e-government needs to focus on the digital empowerment of the community and strengthening trust in the service system used.

Future research is recommended to expand the scope of the study area to test the consistency of this model in various regions with different levels of e-government adoption. In addition, it is necessary to conduct longitudinal research to observe changes in people's attitudes and behavioral intentions over a while to understand the causal relationship more deeply. Exploring other influential variables, such as trust in the system, user satisfaction, or user experience, is also recommended, which can provide a more comprehensive understanding of digital service adoption behavior. Furthermore, the development of measurement instruments that are more contextualized according to local characteristics is also needed so that the research results are more relevant to the needs of the e-government service user community.

## Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation, upon request to the corresponding author.

## Ethics statement

The studies involving human participants were reviewed and approved by the Directorate of Research and Community Service (DPPM), Universitas Islam Riau. The studies were conducted in accordance with local legislation and institutional requirements. All participants provided written informed consent prior to participation.

## Author contributions

KR: Conceptualization, Data curation, Investigation, Project administration, Writing – original draft, Writing – review & editing. RF: Formal analysis, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. ZO: Conceptualization, Resources, Supervision, Validation, Writing – review & editing. SN: Data curation, Writing – review & editing.

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## Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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