An Extended Unified Model of e-Government Adoption: The Role of Trust in Government and Digital Literacy

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ABSTRACT

Digital government transformations are defined by efficiency and accountability. However, their application is frequently interrupted by a lack of institutional trust and varying levels of digital skills among different population groups. This study extends the Unified Model of e-Government Adoption (UMEGA) by adding trust in government and digital literacy as precursors to effort expectancy, attitudes, and intended use. User data from multiple Indonesian public service applications are analyzed with PLS-SEM. The structural model is evaluated with the coefficient of determination (R^2), effect size (f^2), and out-of-sample predictive checks, also establishing measurement reliability and validity. The results revealed that trust and digital literacy raise effort expectancy and foster favorable attitudes toward digital services. Moreover, attitude mediates their effects on intention, while effort expectancy strengthens attitudes, creating an indirect route to intention alongside any direct paths. Overall, the model demonstrates sound explanatory power and credible predictive performance. Policy implications include trust-building through performance transparency, responsive support, and risk communication. In addition, the former involve digital literacy initiatives such as microlearning, inclusive interface design, and omnichannel assistance. Finally, the adoption of privacy-by-design safeguards is highlighted. The findings underscore that socio-psychological determinants are as significant as technical attributes for accelerating inclusive e-government adoption, particularly in developing contexts where user heterogeneity and service diversity demand integrated, user-sensitive approaches.

Keywords-UMEGA; digital literacy; e-government adoption; PLS-SEM

I. INTRODUCTION

The benefits of e-government include improved transparency, efficiency, and higher quality of services provided to citizens [1]. However, for the transition to be successful, developing digital skills within the population and trust in public institutions is required. Despite properly designed digital platforms, e-government needs time and effort to be introduced to the public. Considering the inequality in digital skills, access to digital tools remains exclusive to people already familiar with them [2]. Poor trust in public institutions, combined with low digital skills, obstructs the efficiency and transparency of the system [3]. For e-government to work, institutional trust and digital literacy need to be developed simultaneously. Traditional elements of adopting technology, such as perceived usefulness, ease of use, and organizational environment, are important [4].

Citizens' trust in government directly increases the intention of using e-government services, beyond purely technical readiness [5]. Authors in [6] revealed that effective e-government use can revitalize trust via more positive evaluations of digital service performance. Nevertheless, vulnerable groups experience lower levels of adoption, while diffusion across service channels remains uneven [2].

Authors in [7] proposed a multidimensional approach that integrates both technical and socio-psychological determinants. However, tests that simultaneously place trust in government and digital literacy within the UMEGA framework are limited. Cross-country comparative evidence shows that service performance ratings, trust levels, and the digital divide influence usage [3]. Nonetheless, many analyses are conducted at the aggregate level, resulting in the loss of these latent relationships at the individual level in UMEGA. Implementation research in [8] revealed that digital transformation identifies user competence and trust as key drivers, yet their separate treatment results in fragmented policy recommendations. Additionally, tensions between user-centered design and public value considerations require models more sensitive to user heterogeneity, as addressed by UMEGA through trust and digital literacy [9].

Attitude and trust are the most important aspects in e-government adoption [10]. In the current study, the structural model of e-government adoption will be verified. The model refers to an extended version of UMEGA that incorporates trust in the government and digital literacy. The model evaluates both directly and indirectly the effect of those factors on effort expectancy, attitudes, and behavioral intention. UMEGA's core constructs—performance expectancy, effort expectancy, social influence, and facilitating conditions—serve as the baseline, which is extended by introducing trust in government and digital literacy to reflect the current context of public service delivery [11]. This conceptual model is empirically validated using Partial Least Squares–Structural Equation Modeling (PLS-SEM), which deals with complicated interactions between multiple latent constructs and deriving evidence-based recommendations. The practical significance lies in devising policy initiatives to improve the users' trust and digital skills while taking care of their privacy considerations, which are likely to hamper their adoption [12].

II. THEORETICAL BACKGROUND AND CONCEPTUAL FRAMEWORK

A. UMEGA

This study adopts the UMEGA as the theoretical baseline model. UMEGA positions citizens' beliefs as primary drivers of adoption outcomes. According to UMEGA, the beliefs of the citizens become the major determinants of adoption outcomes. The model uses performance expectation, effort expectation, social influence, and facilitating conditions. These constructs explain how perceived benefits, required effort, normative pressures, and resource availability shape evaluations of digital public services. The proposed framework, thereby, links cognitions to attitudes and behavioral intention in a manner suitable for public administration.

Particularly, performance expectancy relates to the level of belief of the individual concerning the improvement that will be achieved through the application of the service. Effort expectancy entails the level of ease of learning the service and its subsequent application by the user. Social influence relates to the perceived social expectation from people who matter on the use of the service. Facilitating conditions refer to the availability of means, both physical and skill-related, that enhance the process of interaction.

B. Model Extensions: Trust and Digital Literacy

In this study, UMEGA is extended by introducing trust in government and digital literacy as proximal precursors. Trust in government denotes citizens' beliefs about institutional competence, integrity, and benevolence. High trust reduces perceived risk and increases confidence that service performance will be reliable and fair. Digital literacy denotes users' ability to locate, evaluate, and use information and services online. High literacy typically elevates perceived ease and clarifies perceived benefits. These two antecedents, therefore, operate as upstream levers that strengthen expectancy beliefs and attitudes [13].

The proposed relationships follow a disciplined causal logic. Trust in government improves effort expectancy because confident users perceive fewer barriers during interaction with public platforms. Trust also improves attitude because confidence in institutional reliability translates into favorable global evaluations of services. Digital literacy improves effort expectancy because skilled users experience lower cognitive load during task execution. It additionally improves attitude because competent navigation reveals the usefulness of the service in practice. Performance expectancy contributes to attitude because expected benefits raise evaluative judgments of value. Effort expectancy contributes to attitude because perceived ease fosters comfort and reduces anxiety during use. Attitude finally increases behavioral intention because favorable evaluations translate into willingness to engage with services.

These propositions yield a compact set of testable hypotheses. The model predicts positive paths from performance expectancy and effort expectancy to attitude. The model predicts a positive path from attitude to behavioral intention. The model further predicts mediation whereby attitude transmits the effects of trust and digital literacy to intention. This mediational structure reflects the view that socio-psychological determinants operate through global evaluations before shaping intentions.

In this study, effort expectancy functions as a mediator rather than an independent predictor, transmitting the influence of trust in government and digital literacy on attitude and behavioral intention.

C. Conceptual Paths and Hypotheses

The model suggests a sequential causal relationship. The antecedent conditions that act as contextual factors (trust in government and digital literacy) affect the expectancy perceptions of users, especially effort expectancy. The cognitive judgments formed determine the attitude towards the use of technology, and attitude then determines the intention. This causal order is based on technology adoption theory.

In terms of theoretical justification, trust and digital literacy enhance effort expectancy and attitude, with attitude being the primary mediator of intention. Moreover, performance expectancy and effort expectancy affect attitude as well. Direct effects on intention are considered possible when theoretically appropriate. Therefore, this study tests the following compact set of hypotheses. Institutional trust and the digital skills of citizens influence perceptions and evaluations of e-government service delivery. These constructs are considered context variables to augment the UMEGA framework and to be analyzed via their influence on the tested structural paths in the model estimation. Consequently, hypotheses based on the tested structural model are proposed and analyzed only.

The hypotheses stated below correspond strictly to the structural paths specified in the estimated model. Relationships discussed in the theoretical background but not included in the empirical specification are treated as contextual assumptions rather than testable hypotheses, ensuring consistency between the conceptual framework and the statistical analysis.

- H1: Trust in government leads to effort expectancy
- H3: Digital literacy leads to effort expectancy
- H5: Effort expectancy leads to attitude
- H6: Performance expectancy leads to attitude
- H7: Attitude leads to behavioural intention

While both theoretical frameworks exhibit possible direct impacts on attitude, the ultimate structural model identifies these factors as distal antecedents that exert their effects on attitude indirectly via effort expectancy. This approach is consistent with the extended UMEGA paradigm, wherein distal factors exert indirect impacts on attitudes via the mechanism of cognitive evaluations. Therefore, only paths included in the estimation process of the structural model can be regarded as testable hypotheses.

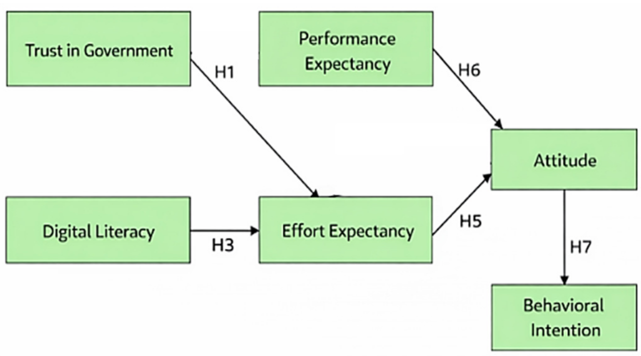

Fig. 1. Extended UMEGA structural model.

Figure 1 illustrates the extended UMEGA and consolidates the hypothesized paths. The configuration supports coherent estimation using PLS-SEM and facilitates clear interpretation of direct and mediated effects. Figure 1, thus, provides a compact map for the empirical tests that follow.

III. METHODOLOGY

In this study, an explanatory quantitative design with a cross-sectional survey was adopted through the application of PLS-SEM to validate the extended UMEGA model in relation to e-government adoption in Indonesia [14].

Online data were collected from Google forms during the period from July 2024 to December 2024 based on a Likert scale questionnaire administered to the users of four government service apps in Indonesia, namely SISTER (Sistem Informasi Sumber Daya Terpadu), e-Imigrasi, PeduliLindungi, and Samsat Digital Nasional (SIGNAL). All construct items were modified after relevant literature reviews and translated when necessary. Indicator reliability, internal consistency (based on Cronbach's alpha and Composite Reliability (CR)), convergent validity (based on outer loadings and Average Variance Extracted (AVE) ≥ 0.50), discriminant validity (Heterotrait–Monotrait ratio (HTMT)) and bootstrapped Confidence Intervals (CI)), and multicollinearity (VIF) were assessed for the measurement model, whereas R^2, f^2, Q^2/PLS-Predict, and bootstrapping were utilized to assess the structural model to determine significant paths and mediating effects of attitude [15-17].

Figure 2 summarizes the quantitative research procedure, starting from theory review and model specification, followed by instrument development, survey data collection, PLS-SEM analysis (measurement and structural models), and model validation for policy interpretation. Specifically, stage 1 (preparation) refers to a focused literature review on TAM, TPB, UTAUT, and UMEGA to identify gaps and derive the extended conceptual framework for the Indonesian e-government context. In stage 2 (research design), constructs and indicators were operationalized, the questionnaire was developed and validated (content/face validity), and the sampling and survey administration plan was finalized. Moreover, during data collection (stage 3), survey responses were collected from users of the four e-government applications via an online questionnaire. In stage 4 (data analysis), PLS-SEM analysis was conducted in two steps. Initially, the measurement model was evaluated (reliability and validity), and subsequently, the evaluation of the structural model was performed (hypothesis testing, explanatory power, and predictive relevance). In stage 5 (model establishment), the final model specification and policy implications were derived from the validated PLS-SEM results to inform interventions for trust-building and digital-literacy strengthening.

The reflective measurement model was assessed for reliability, convergent and discriminant validity (with HTMT inference confirmed via bootstrapped CIs), and multicollinearity prior to structural model assessment.

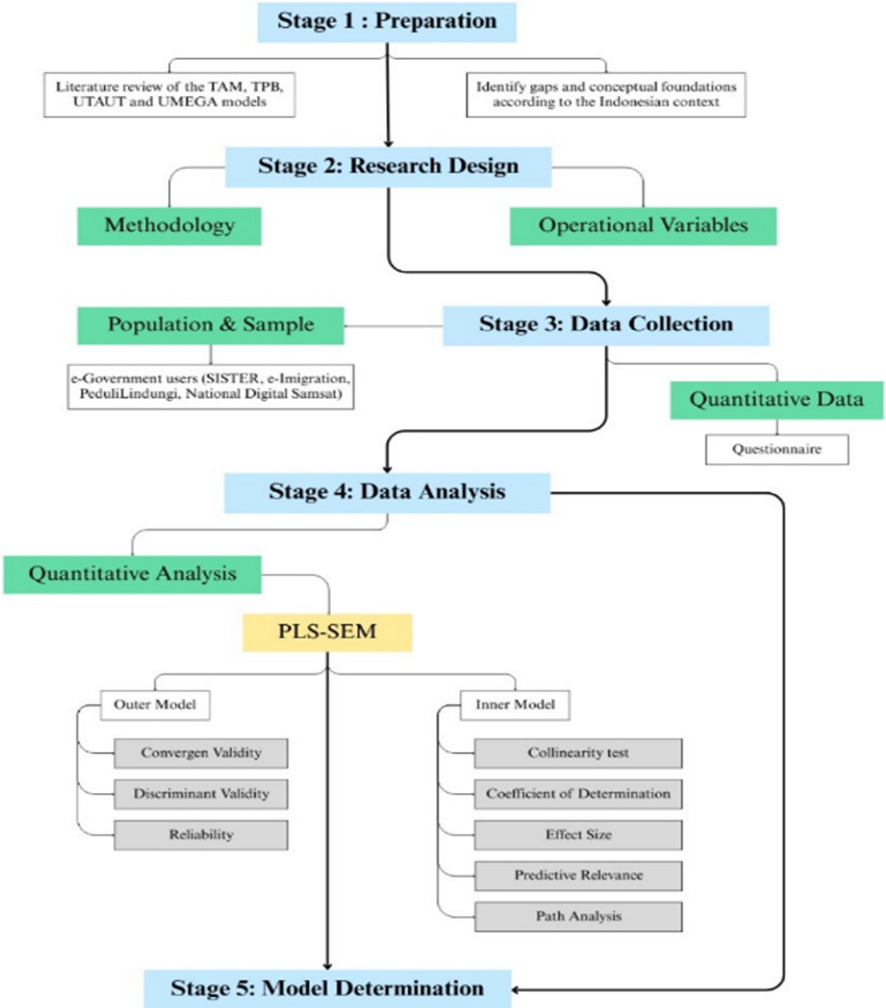

Fig. 2. Research framework and analytical procedure for validating the extended UMEGA model, including model specification, data collection, measurement evaluation, and structural testing.

IV. RESULTS

A. *Outer Model*

The outer model or measurement model represents the correlation between latent constructs and their measures. The evaluation of the outer model seeks to establish the validity and reliability of the constructs prior to evaluating the inner model. For the reflective models, this evaluation involves indicator reliability, internal reliability, convergent validity, and discriminator validity. Formative models' evaluation entails the assessment of indicator weight significance and multicollinearity.

Convergent validity in this study is measured construct-wise before presenting item loadings and AVE. The AVE method is used to measure convergent validity based on the criteria of at least 0.50 for a construct to be valid. Constructs that fall short of the criteria but meet CR and consistency can still be included in the model if theoretically justified [18].

Reliability of the indicators was determined using outer loadings. According to the criteria, an outer loading of 0.708 or higher implies that the indicator explains more than 50% of the variance of the construct. Outer loadings of 0.60-0.70 were retained if they were theoretically necessary, and the construct reliability was adequate. Outer loadings of 0.60 or lower were excluded during the measurement model refinement phase for better AVE scores.

Construct validity was enhanced through the careful evaluation of low-loading indicators that contributed minimally to convergent validity. If theoretically justified, the problematic indicators were excluded or modified, and the model was estimated again. The final measurement model exhibits better reliability and convergent validity without compromising the adequacy of the constructs' conceptual domains.

1) AVE

AVE is utilized for measuring the validity of reflective constructs’ convergence. As part of refining the measurement model, indicators with marginal loadings can either be retained or dropped if their constructs have an adequate level of AVE. In addition, the square root of AVE is utilized within the Fornell–Larcker criteria for evaluating discriminant validity, forcing the former to be greater than inter-construct correlations. Since a satisfactory AVE was detected across all constructs, the measurement model was valid for further testing of the structural model. To solve the problem of marginal AVE, refinement of items was performed by considering the values of their loadings, cross-loading, and conceptuality. Some indicators were dropped or kept, depending on the theoretical background of the construct. For ease of presentation, the constructs are abbreviated as: M1 refers to attitude, M2 to effort expectancy, X1–X7 to exogenous constructs, and Y to behavioral intention. These labels correspond directly to the conceptual variables defined in the model. According to Table I, several constructs exhibit AVE values close to but slightly below the 0.50 guideline.

TABLE I. AVE VALUES PER CONSTRUCT

Var	AVE
X1	0.520
X2	0.473
X3	0.449
X4	0.474
X5	0.492
X6	0.503
X7	0.458
M1	0.497
M2	0.473
Y	0.494

Following PLS-SEM reporting guidance, the results are interpreted together with indicator loadings and CR. Low-loading indicators were re-checked and measurement items were refined to improve convergent validity while preserving theoretical coverage; the updated AVE values are reported in Table I. Construct consolidation was considered but not used, since each construct is theoretically unique in the expanded UMEGA model. Combining constructs would reduce conceptual clarity and limit comparability with prior adoption research. Instead, refinement focused on improving indicator quality while preserving the theoretical structure of the model.

2) HTMT

Discriminant validity was evaluated using the HTMT ratio. It compares correlations across constructs to correlations within constructs for each construct pair. In practice, HTMT values are deemed acceptable if they fall below 0.90 (or 0.85 under a more conservative criterion). Following the original procedure, this work also inspected the 95% bootstrap CI; discriminant validity is supported when the upper bound remains below the chosen threshold (and below 1.00). This study reports the maximum HTMT value and, if any pair exceeds the proposed limit, re-specification is considered via indicator revision/removal or construct refinement [19].

Table II shows that most HTMT values are below the commonly used cut-offs (0.85–0.90). However, before refinement, the X2–M2 construct pair produced an HTMT value exceeding 1.0 (HTMT = 1.162), indicating insufficient discriminant validity and potential conceptual/indicator overlap. Therefore, the indicators of both constructs were examined by inspecting outer loadings, cross-loadings, and item wording similarity. Then, the measurement model was refined by removing/revising the indicator(s) contributing most to the overlap. The model was subsequently re-estimated, and HTMT was reassessed using both the updated HTMT matrix and HTMT inference (bootstrapped CIs). The revised results support discriminant validity, as HTMT values meet the selected criterion and the corresponding CI does not include 1.0.

TABLE II. HTMT MATRIX (DISCRIMINANT VALIDITY; CUT-OFFS 0.85–0.90)

	M1	M2	X1	X2	X3	X4	X5	X6	X7	Y
M1	-	-	-	-	-	-	-	-	-	-
M2	0.847	-	-	-	-	-	-	-	-	-
X1	0.859	0.865	-	-	-	-	-	-	-	-
X2	0.847	1.162	0.865	-	-	-	-	-	-	-
X3	0.819	0.790	0.832	0.790	-	-	-	-	-	-
X4	0.771	0.913	0.771	0.913	0.772	-	-	-	-	-
X5	0.090	0.117	0.090	0.117	0.118	0.206	-	-	-	-
X6	0.749	0.554	0.644	0.554	0.720	0.482	0.193	-	-	-
X7	0.782	0.878	0.782	0.878	0.734	0.943	0.193	0.511	-	-
Y	0.956	0.805	0.845	0.805	0.836	0.726	0.089	0.744	0.767	-

Reliability is a measure of internal consistency that indicates the extent to which indicators in a construct can provide stable and consistent results in measurements. In this study, reliability testing was conducted using two approaches, namely Cronbach's alpha and CR. The results of Cronbach's alpha and CR testing are presented in Table III. Based on Table III, the results of the Cronbach's alpha test show that all research variables have values above 0.70, indicating good internal consistency. The variable performance expectancy has a Cronbach's alpha value of 0.884, an effort expectancy value of 0.861, a social influence value of 0.845, and a facilitating condition value of 0.860. Meanwhile, the variable perceived risk obtained a value of 0.890, a trust in government value of 0.877, and a digital literacy value of 0.851. For the mediation variables, attitude has a value of 0.873, and effort expectancy has a mediation of 0.861. The dependent variable, behavioral intention, has a Cronbach's alpha value of 0.871. These values indicate that each construct has strong reliability in measuring its indicators.

The outer model was evaluated using indicator loadings, AVE, HTMT, and reliability metrics. Wherever diagnostics indicated issues, item refinement was applied guided by theory and empirical diagnostics, and the revised results are presented in the updated tables. The following diagnostic procedures at an indicator level were performed to resolve issues arising out of high HTMT value between X2 and M2 (loadings, cross-loadings, and conceptual overlap). Once the issue was addressed by eliminating or modifying those indicators that were causing issues, a re-estimation of the model yielded satisfactory HTMT results. The refinement process did not alter the theoretical meaning of the constructs, as only indicators contributing to measurement redundancy were modified or removed. Each construct retained sufficient indicators to represent its conceptual domain within the extended UMEGA framework.

TABLE III. CRONBACH'S ALPHA AND CR

	Cronbach's alpha	CR (rho_c)
X1	0.884	0.907
X2	0.861	0.890
X3	0.845	0.879
X4	0.860	0.890
X5	0.890	0.895
X6	0.877	0.901
X7	0.851	0.883
M1	0.873	0.899
M2	0.861	0.890
Y	0.871	0.897

B. *Inner Model*

Consistent with the conceptual framework, effort expectancy is interpreted as a mediating construct linking contextual antecedents to attitude and behavioral intention rather than as an independent driver. The following analysis emphasizes the substantive interpretation of relationships among constructs rather than reiterating statistical criteria, highlighting what the results imply for e-government adoption behavior. The inner model or structural model is used to test the relationship between latent variables and evaluate the overall quality of the research model. The stages of inner model analysis include:

1) *Collinearity Test*

The R² results indicate that the proposed structural model demonstrates strong explanatory power for the endogenous constructs. Specifically, as presented in Table IV, the model explains 66.6% of the variance in M1 (R^2 = 0.666; adjusted R^2 = 0.664), 67.7% of the variance in M2 (R^2 = 0.677; adjusted R^2 = 0.674), and 71.2% of the variance in Y (R^2 = 0.712; adjusted R^2 = 0.711). These values suggest that the predictors included in the model account for a substantial proportion of the variance in the key outcomes, leaving a relatively smaller share attributable to factors outside the model. Moreover, the very small differences between R^2 and adjusted R^2 across all endogenous variables indicate that the explained variance is stable and not artificially inflated by the number of predictors, supporting the robustness of the model's explanatory capability.

TABLE IV. R² OF THE STRUCTURAL MODEL

	R^2	Adjusted R^2
M1	0.666	0.664
M2	0.677	0.674
Y	0.712	0.711

Although these results are sometimes presented within a broader structural-model evaluation, it is important to distinguish them from collinearity diagnostics. Collinearity should be assessed using inner VIF values, whereas R² belongs to the structural model assessment under the R² criterion.

2) *Effect Size (f^2)*

The f^2 is used to measure the contribution of each independent variable in explaining the dependent variable in a structural model. The f^2 value shows how much the R^2 value of the dependent construct changes when one independent construct is removed from the model. The greater the f^2 value, the stronger the influence of that construct on the target construct. Based on the interpretation guidelines, f^2 values are categorized as small (≥ 0.02), medium (≥ 0.15), and large (≥ 0.35). The effect size measurements for each relationship between constructs are presented in Table V.

TABLE V. EFFECT SIZE

	M1	M2	X1	X2	X3	X4	X5	X6	X7	Y
M1	-	-	-	-	-	-	-	-	-	0.782
M2	-	-	-	-	-	-	-	-	-	0.054
X1	0.112	-	-	-	-	-	-	-	-	-
X2	0.054	-	-	-	-	-	-	-	-	-
X3	0.073	-	-	-	-	-	-	-	-	-
X4	0.008	0.253	-	-	-	-	-	-	-	-
X5	-	0.001	-	-	-	-	-	-	-	-
X6	-	0.048	-	-	-	-	-	-	-	-
X7	-	0.087	-	-	-	-	-	-	-	-
Y	-	-	-	-	-	-	-	-	-	-

According to Table V, the f^2 results show that M1 is the most influential predictor of Y with an f^2 value of 0.782, while M2 has only a weak effect (f^2 = 0.054). For the mediating paths, X1 and X3 contribute moderate effects on M1 (f^2 = 0.112 and 0.073, respectively), whereas X2 is weak (f^2 = 0.054). In addition, X4 are negligible for M1 (f^2 = 0.008) but moderate for M2 (f^2 = 0.253). Other effects on M2 are minimal, including X5 (f^2 = 0.001) and X6 (f^2 = 0.048), while X7 is small-to-moderate (f^2 = 0.087).

3) Predictive Relevance - Q^2

Q^2 testing is conducted to assess the predictive ability of structural models in PLS-SEM. The Q^2 value is obtained through:

$$Q^2 = 1 - (SSE/SSO) \quad (1)$$

where SSO is the sum of squares observation, and SSE is the sum of squared errors. The higher the Q-square value, the better the predictive ability of the model for endogenous variables. A Q-square value greater than zero indicates that the model has predictive relevance, while a value close to zero indicates weak predictive ability. For all exogenous variables, Q^2 is equal to zero because they function as predictors and are not predicted by other constructs in the model. In contrast, the endogenous variables show positive Q^2 values, as depicted in Table VI. SSO, SSE, and Q^2 values.

TABLE VI. Q-SQUARE VALUE

	SSO	SSE	Q^2
X1	4.257.000	4.257.000	0.000
X2	4.257.000	4.257.000	0.000
X3	4.257.000	4.257.000	0.000
X4	4.257.000	4.257.000	0.000
X5	4.257.000	4.257.000	0.000
X6	4.257.000	4.257.000	0.000
X7	4.257.000	4.257.000	0.000
M1	4.257.000	2.866.035	0.327
M2	4.257.000	2.912.124	0.316
Y	4.257.000	2.778.256	0.347

These results indicate that the model has moderate predictive relevance for the endogenous constructs, supporting its suitability for explaining the causal relationships in the PLS-SEM structural model. The relevance categories are presented in Table VII. To assess out-of-sample predictive performance, this study ran PLS-Predict with k-fold cross-validation in SmartPLS. Prediction errors for each indicator of the key endogenous constructs are reported and compared against a linear model benchmark.

TABLE VII. Q^2 VALUE CATEGORY

Value range	Relevance category
$0 < Q^2 \leq 0.25$	Low
$0.25 < Q^2 \leq 0.50$	Medium
$Q^2 > 0.50$	High

4) Path Analysis

Table VIII presents the path coefficient analysis and the magnitude of direct effects among variables in the structural model. The mediating variable M1 shows the strongest statistically significant positive effect on behavioral intention, with a coefficient of 0.699 and a t-statistic of 16.155. Therefore, the users' attitudes play a dominant role in strengthening behavioral intention in the context of e-government service adoption.

Effort expectancy as a mediating variable also exerts a positive influence on behavioral intention, with a coefficient of 0.184 and a t-statistic of 3.958. Overall, the results suggest that both mediators are important in driving users' behavioral intention to utilize e-government services, with attitude emerging as the more influential factor.

TABLE VIII. PATH COEFFICIENT ANALYSIS

	Original sample (O)	Sample means (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	p-values
M1 - Y	0.699	0.701	0.043	16.155	0.000
M2 - Y	0.184	0.183	0.047	3.958	0.000
X1 - M1	0.330	0.325	0.062	5.291	0.000
X2 - M1	0.252	0.253	0.060	4.228	0.000
X3 - M1	0.245	0.249	0.049	5.010	0.000
X4 - M1	0.085	0.085	0.063	1.335	0.182
X4 - M2	0.494	0.489	0.045	10.942	0.000
X5 - M2	-0.022	-0.010	0.029	0.741	0.458
X6 - M2	0.146	0.152	0.034	4.345	0.000
X7 - M2	0.292	0.290	0.048	6.016	0.000

5) Summary Test

Bootstrapping with a one-tailed test was used to assess the significance of the structural paths. A relationship is considered significant when $t > 1.645$ at $\alpha = 0.05$. Table IX displays the β, t, p values, and support status for the tested hypotheses. This subsection reports the hypothesis-testing results only for structural paths that were explicitly specified and estimated in the PLS-SEM model. Accordingly, all hypotheses presented here correspond directly to paths with available bootstrapping statistics (β, t, p values), ensuring consistency between the conceptual model and the estimation output. As shown in Table IX, all five hypotheses are supported, with all paths reaching statistical significance under the one-tailed bootstrapping test.

According to Table IX, the hypothesis testing results are reported only for structural paths that were explicitly specified and estimated in the PLS-SEM model. The tested paths show significant and positive effects across the model. H7 presents the strongest relationship (β = 0.699; t = 16.155; p value = 0.000), indicating that citizens' intention to use e-government services is primarily driven by their attitude. In addition, H5 (β = 0.252; t = 4.228; p value = 0.000) and H6 (β = 0.330; t = 5.291; p value = 0.000) significantly strengthened attitude. At the antecedent level, H1 (β = 0.146; t = 4.345; p value = 0.000) and H3 (β = 0.292; t = 6.016; p value = 0.000) are also significant, suggesting that trust and citizens' digital capability enhance perceived ease of using the services, which then contributes to a more favorable attitude and stronger intention.

TABLE IX. HYPOTHESIS TESTING RESULT SUMMARY FROM BOOTSTRAPPING

Hypothesis	Structural Path	β	t	p-value
H1	Trust in Government → Effort Expectancy	0.146	4.345	0.000
H3	Digital Literacy → Effort Expectancy	0.292	6.016	0.000
H5	Effort Expectancy → Attitude	0.252	4.228	0.000
H6	Performance Expectancy → Attitude	0.330	5.291	0.000
H7	Attitude → Behavioral Intention	0.699	16.155	0.000

V. DISCUSSION

From a comparative perspective, the explanatory power obtained for behavioral intention (R^2 = 0.712) is at the upper range of many UMEGA/UTAUT extensions reported in the literature, often explained at moderate levels depending on context and model scope [3, 8]. This suggests that combining socio-psychological antecedents, such as trust in government and digital literacy, with expectancy-attitude mechanisms provides a particularly effective specification for diverse e-government services. A comparable UMEGA validation study reported 46.6% variance explained in behavioral intention [20], suggesting that the integration of socio-psychological antecedents offers a particularly effective specification for diverse e-government services.

First, the constructs with the largest effects on adoption (based on the absolute standardized path coefficients $|\beta|$ and the f^2 effect sizes) should be treated as the most actionable levers for practice. For instance, if ease of use or facilitating conditions emerge as dominant, the implication is to prioritize user experience improvements, clearer step-by-step guidance, and reliable support channels.

Second, if trust in government shows a significant effect, this suggests that adoption is shaped by perceived institutional integrity, competence, and risk reduction. In heterogeneous public-service settings, users may interpret government-backed platforms as higher-stakes systems, so transparency, data protection assurances, and consistent service performance become central. If the effect is weak or non-significant, a plausible interpretation is that users' decisions are driven more by direct service utility and usability than by institutional perceptions in this sample.

Third, digital literacy can be understood as a capability prerequisite: users who can navigate digital information and interfaces are more likely to convert intention into sustained use. Practically, this points to the value of inclusive design (plain language, accessible layouts), contextual help, and onboarding materials that reduce cognitive load for lower-literacy segments.

Fourth, for constructs that are weak or non-significant, the manuscript discusses plausible contextual explanations (e.g., mandatory or habitual use, limited variability in the sample, or service-specific constraints), and considers measurement factors that may attenuate effects (e.g., indicators with low loadings that reduce AVE).

Finally, the contribution of this study is to extend UMEGA by incorporating trust in government and digital literacy as antecedents relevant to public digital services in Indonesia. The policy implication is that adoption is not only a matter of feature delivery, but also of institutional credibility and user capability—highlighting the importance of transparency initiatives and inclusive, literacy-sensitive service design to reduce barriers to use.

VI. LIMITATIONS AND FUTURE RESEARCH

Despite its contributions, this study highlighted several limitations. Initially, the cross-sectional design captures perceptions at a single point in time and does not allow causal inference regarding changes in attitudes or intentions over time. Longitudinal studies would provide deeper insights into adoption dynamics. Second, the use of self-reported survey data introduces the possibility of common-method bias. Although procedural remedies were applied during questionnaire design, future research may employ multi-source data or behavioral measures to strengthen validity. Third, the findings are based on users of selected Indonesian e-government applications, which may limit generalizability to other institutional or cultural contexts. Comparative cross-country studies could provide broader validation of the extended UMEGA framework. Future research may also explore additional moderators, such as demographic characteristics, service type, or policy environment, to better understand heterogeneous adoption patterns.

VII. CONCLUSIONS

This study is motivated by the need to understand the factors that influence individual behavior in the context of technology adoption, particularly in relation to variables such as performance expectations, effort expectations, social influence, supportive conditions, digital literacy, perceived risk, and trust in the government. The conceptual framework of this study emphasizes the importance of evaluating the extent to which these factors play a role in shaping people's attitudes and behavioral intentions. In the present study, a Partial Least Squares- Structural Equation Modeling (PLS-SEM) model was used as an approach to test the validity and reliability of constructs and to test the relationships between latent variables.

The PLS-SEM method was chosen because it can handle models with complex constructs and multiple indicators and is more flexible in dealing with limited sample sizes and non-normal data distributions. The evaluation was conducted in two stages, namely the outer model, which focused on measurement validity and reliability, and the inner model, which tested the relationship between latent constructs. Various criteria, such as Average Variance Extracted (AVE), Heterotrait–Monotrait ratio (HTMT), Cronbach's alpha, Composite Reliability (CR), coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2), were used to ensure the reliability and predictive relevance of the research model.

The analysis results show that although some constructs have AVE values slightly below the threshold of 0.50, the Cronbach's alpha and CR values are well above the minimum criteria, so the model can still be declared valid and reliable. Discriminant testing through HTMT showed that the constructs could be distinguished well, while structural testing on the inner model showed adequate explanatory power (R^2), significant effects (f^2), and predictive relevance (Q^2). Overall, the findings of this study support the proposed conceptual model, they provide empirical evidence regarding the factors that influence behavioral intentions, and reinforce the theoretical contributions and practical implications in developing technology adoption strategies.

DECLARATION OF COMPETING INTERESTS

Not applicable to this work.

DATA AVAILABILITY STATEMENT

The dataset supporting the findings of this study is publicly available at [21]. The dataset has been anonymized and made publicly accessible to support transparency and reproducibility.

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