From Technophobia to Digital Adoption: Reconstructing the Utaut Model with Digital Literacy Moderation Among Older Adults for Inclusive Public Services

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Abstract Despite the rapid acceleration of digital transformation, the digital divide among older adults remains a significant barrier to inclusive public services. This study addresses this gap by reconstructing the Unified Theory of Acceptance and Use of Technology (UTAUT) model, integrating Digital Literacy as a moderator and evaluating the impact of Technophobia on technology adoption behavior. Data were collected from a sample of older adults and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results indicate that the reconstructed model possesses a substantial explanatory power, with an R^2 of 0.835 for Actual Use. Findings reveal that Social Influence and Effort Expectancy are the most significant drivers of Behavioral Intention, which subsequently serves as a robust mediator for actual usage. Crucially, the moderation analysis highlights that Digital Literacy significantly bridges the intention-behavior gap, whereas Technophobia yields a negligible effect size ($f^2 = 0.000$), suggesting that technical competence is a more critical determinant than psychological fear in this demographic. These results challenge traditional stereotypes and emphasize that achieving digital inclusion requires a strategic shift from anxiety-reduction to competence-building. The study provides a novel theoretical framework for understanding senior digital engagement and offers practical recommendations for policymakers to design age-friendly, cognitively accessible digital public services. This research concludes that fostering social support networks and enhancing digital literacy are the most effective paths toward bridging the digital adoption gap in an aging society.

Keywords: UTAUT Reconstruction; Digital Literacy; Technophobia; Older Adults; Digital Inclusion

INTRODUCTION

The rapid digitalization of public administration has fundamentally redefined the interface between the state and its citizens. In the pursuit of efficiency and transparency, e-government systems have shifted from supplementary channels to the primary infrastructure for public service delivery (Balaskas, 2022). However, this "digital-by-default" paradigm risks marginalizing vulnerable groups, most notably older adults. As global populations age, ensuring inclusive public services becomes a social necessity and a critical benchmark for successful democratic governance.

Despite the proliferation of digital platforms, a persistent "digital divide" separates the silver generation from the benefits of electronic services (König & Seifert, 2023). While governments invest heavily in technical architecture, human-centric barriers, particularly the psychological resistance known as "technophobia" remain largely unresolved (Hayes, 2018). For older adults, the transition to digital platforms is frequently marred by anxiety and a perceived lack of self-efficacy, creating a formidable barrier to the realization of universal public access.

The Unified Theory of Acceptance and Use of Technology (UTAUT) serves as the gold standard for understanding technology adoption (Venkatesh et al., 2003). By identifying

performance expectancy, effort expectancy, social influence, and facilitating conditions as drivers, it provides a robust framework for predicting intentions. However, a limitation exists in its assumption that strong behavioral intention (IU) automatically translates into actual use (AU). In the elderly context, this path is often disrupted, suggesting a significant "intention-behavior gap." The Venkatesh et al. (2003) UTAUT model is described as follows:
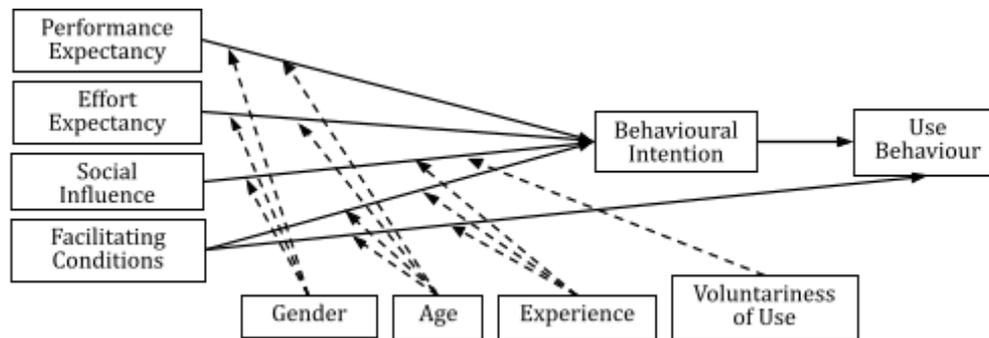

Figure 1. Theoretical Framework

This research addresses a pivotal theoretical gap by examining the transition from intention to Actual Use (AU) among older adults. While standard UTAUT studies focus on predictors of intention, they often overlook the moderating forces that catalyze or inhibit behavioral execution. This study proposes a reconstructed model introducing Digital Literacy (DL) (Bongomin et al., 2025; Syafitri et al., 2024; Tulcanaza-Prieto et al., 2025) and Technophobia (TP) (Novitasari & Widayani, 2025) as dual moderators of the Intention-to-Use (IU) and AU relationship.

Theoretically, this positioning contends that digital literacy provides the cognitive scaffolding necessary to translate willingness into action (Hildawati et al., 2024). Conversely, technophobia acts as a psychological inhibitor, creating "friction" that can neutralize motivation (Hayes, 2018). By scrutinizing these interactions, the study offers a nuanced framework for understanding how cognitive competencies and psychological barriers dictate the success of digital adoption in inclusive public services.

Digital literacy is conceptualized here as the cognitive confidence that empowers older adults to navigate complex environments (Hildawati et al., 2021). When a citizen possesses high digital literacy, the bridge between intention and actual use is strengthened, providing the resilience to overcome technical hurdles. By examining DL as a moderator, this study moves beyond treating literacy as a mere prerequisite, viewing it instead as a dynamic enabler that determines the success of the digital adoption journey (Bongomin et al., 2025).

Simultaneously, the role of Technophobia as a negative moderator provides a critical affective dimension. Technophobia is not merely an absence of skill, but a presence of dread that distorts decision-making. By analyzing TP as a moderator, this research seeks to explain why many older adults who intend to use e-government services ultimately retreat at the point of execution. Understanding this inhibitory effect is crucial for designing empathetic interfaces and psychological support systems.

Ultimately, this article contributes theoretically by bridging the intention-behavior gap through a dual-moderation lens. Practically, it offers a roadmap for policymakers to move toward human-centric digital strategies. Utilizing Partial Least Squares Structural

Equation Modeling (PLS-SEM), this research provides empirical rigor to ensure that the digital future of public services honors and includes every citizen, regardless of age.

CONCEPTUAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

The conceptual framework of this study integrates the core constructs of the Unified Theory of Acceptance and Use of Technology (UTAUT) with Digital Literacy as a moderating variable. This reconstruction aims to explain the transition from technophobic tendencies to digital adoption among the elderly. We argue that while the four UTAUT pillars provide the "motivation" for adoption, digital literacy acts as the "enabler" that determines the strength of these motivational forces. The research framework is described as follows:
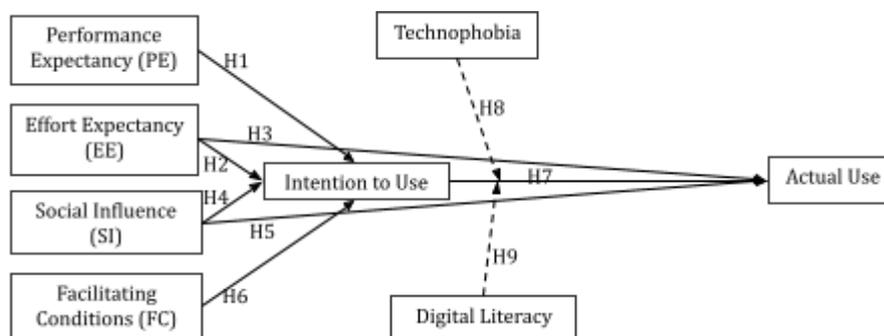

Figure 2. Research Framework

1. Performance Expectancy and Digital Adoption

Performance expectancy (PE) is defined as the degree to which an individual believes that using an e-government service will provide benefits in performing certain activities (Afrizal et al., 2023; Tang, 2021). For older adults, these benefits often include time-saving in bureaucratic processes or easier access to health and social services. In an era of digital-first public services, the perceived utility of a system is a primary driver of adoption.

H1: Performance Expectancy (PE) has a significant positive influence on Intention to Use (IU) of digital in older adults.

2. Effort Expectancy and Digital Adoption

Effort expectancy (EE) refers to the perceived ease of use associated with technology (Osei, 2022). Older adults often face cognitive and physical limitations (e.g., declining vision or motor skills) that make complex interfaces daunting. If the digital service is perceived as user-friendly and requires minimal mental effort, the barrier of technophobia can be lowered significantly.

H2: Effort Expectancy (EE) has a significant positive influence on Intention to Use (IU) of digital in older adults.

H3: Effort Expectancy (EE) has a significant positive influence on Actual Use (AU) of digital in older adults.

3. Social Influence and Digital Adoption

Social influence (SI) represents the extent to which an individual perceives that important others (family, peers, or community leaders) believe they should use the new system (Hassan, 2022). In many cultures, older adults rely heavily on the opinions and

assistance of their children or grandchildren. Positive social pressure can act as a catalyst to overcome initial resistance to digital platforms.

H4: Social Influence (SI) has a significant positive influence on Intention to Use (IU) of digital in older adults.

H5: Social Influence (SI) has a significant positive influence on Actual Use (AU) of digital in older adults.

4. Facilitating Conditions and Digital Adoption

Facilitating conditions (FC) encompass the objective factors in the environment that make an action easy to accomplish, such as having a stable internet connection, appropriate hardware, and technical support (Hassan, 2022). For the elderly, the availability of "digital help-desks" or simplified manuals is critical in ensuring that their intention to use technology is translated into actual behavior.

H6: Facilitating Conditions (FC) has a significant positive influence on Intention to Use (IU) of digital in older adults.

5. The Mediating Role of Intention to Use

In the architecture of technology adoption, Intention to Use (IU) serves as the critical cognitive nexus transforming external perceptions into tangible actions (Shahzad et al., 2022). Drawing from the Unified Theory of Acceptance and Use of Technology (UTAUT), this study proposes that the influence of its four primary pillars on Actual Use (AU) is internally mediated by behavioral intention. For older adults, this mediation represents a "mental commitment" phase, where the perceived benefits and accessibility of e-government services are synthesized into a conscious decision to engage.

This mediating role is essential due to the complexity of elderly digital adoption. Perceived utility or ease of use does not spontaneously trigger usage; instead, these factors cultivate a state of readiness. Behavioral intention acts as the motivational engine that converts theoretical perceptions into active engagement. Without this essential conduit, the UTAUT pillars remain dormant, failing to bridge the gap between cognitive appraisal and actual behavioral execution.

H7: Intention to Use (IU) has a significant positive influence on Actual Use (AU) of digital in older adults.

H7a: Intention to Use (IU) significantly mediates the relationship between Performance Expectancy (PE) and Actual Use (AU).

H7b: Intention to Use (IU) significantly mediates the relationship between Effort Expectancy (EE) and Actual Use (AU).

H7c: Intention to Use (IU) significantly mediates the relationship between Social Influence (SI) and Actual Use (AU).

H7d: Intention to Use(IU) significantly mediates the relationship between Facilitating Conditions and Actual Use(AU).

6. The Moderating Role of Technophobia

Technophobia (TP) serves as the critical affective inhibitor in our reconstructed model. We propose that the transition from intention to digital adoption is not merely a cognitive calculation but is heavily suppressed by the psychological friction of technological anxiety (Hayes, 2018). In this context, technophobia acts as a "negative filter" that can diminish or even neutralize the positive drivers of the UTAUT framework.

Technophobia provides a psychological barrier that distorts an individual's processing of technological benefits. For an elderly person with high technophobia, the "benefits" (PE) of e-government may be intellectually recognized but emotionally rejected due to a fear of making errors or compromising security. Similarly, even when a system is objectively easy to navigate (EE), the presence of high technophobia creates a "perceived complexity" that makes the interface feel overwhelming. In essence, technophobia functions as a disruptive force that dictates the threshold at which UTAUT constructs actually translate into adoption.

H8: Technophobia (TP) significantly moderates the relationship between Intention to Use (IU) and Actual Use (AU).

7. The Moderating Role of Digital Literacy

Digital literacy (DL) is the pivotal variable in our reconstructed model. We propose that the impact of UTAUT constructs on adoption intention is not uniform across all elderly individuals; rather, it is contingent upon their level of digital literacy.

Digital literacy provides the cognitive scaffolding that allows an individual to process technological information (Gordon & Hornbrook, 2018). For an elderly person with high digital literacy, the "effort" required (EE) is perceived as even lower, and the "benefits" (PE) are more clearly understood. Conversely, for those with low digital literacy, even a well-designed system may feel insurmountable, thereby weakening the link between performance expectancy and intention. Digital literacy effectively "filters" how technophobia is managed.

H9: Digital literacy significantly moderates the relationship between Intention to Use (IU) and Actual Use (AU).

METHOD

1. Research Design and Paradigm

This study adopts a positivist paradigm with a quantitative-deductive approach to empirically validate a reconstructed UTAUT framework. Utilizing an explanatory research design, the study establishes causal explanations for the "intention-behavior gap" among older adults. This methodology facilitates rigorous testing of Digital Literacy and Technophobia as critical boundary conditions in the trajectory from Intention to Use (IU) to Actual Use (AU), providing a robust theoretical reconstruction of digital adoption dynamics.

A cross-sectional survey methodology was employed to capture elderly behavioral tendencies within the e-government landscape. This design supports Partial Least Squares Structural Equation Modeling (PLS-SEM) (Hair et al., 2024b), which is uniquely robust for testing simultaneous mediation and moderation in predictive models. By prioritizing objectivity and replicability, the framework ensures that findings are grounded in a systematic, statistically sound approach, enhancing validity for high-impact academic dissemination.

2. Sampling Technique and Participants

The target population for this study comprises older adults aged 60 and above, the demographic most impacted by the digital divide. A non-probability purposive sampling technique was employed to select respondents based on specific inclusion criteria (Basiroen et al., 2024; Makwana et al., 2023): possession of digital devices and prior experience or intentional avoidance of e-government platforms. This strategic selection

ensures the data accurately reflects the tension between Intention to Use (IU) and Actual Use (AU), while capturing a broad spectrum of Digital Literacy and Technophobia within the "silver generation."

To ensure robust statistical power, the minimum sample size was determined using G*Power 3.1. Based on 7 predictors and a medium effect size ($f^2 = 0.15$), a minimum of 153 respondents was required to achieve a power of 0.95. The study exceeded this threshold with 176 valid responses, enhancing the stability of the PLS-SEM estimates. Furthermore, a hybrid recruitment strategy combining digital outreach with physical assistance at community centers was utilized to mitigate non-response bias and ensure the sample included both tech-savvy and technophobic individuals, providing a representative dataset for testing the proposed boundary conditions.

3. Instrumentation and Measurement

The measurement instrument was developed by adapting validated scales to ensure contextual relevance for e-government and the elderly demographic. Primary UTAUT constructs Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions were derived from (Venkatesh et al., 2003), while Intention (IU) and Actual Use (AU) scales were tailored from (Yu, 2021). To operationalize the moderators, Digital Literacy (DL) was adapted from (Aavakare & Nikou, 2020), and Technophobia (TP) was measured using indicators from (Novitasari & Widayani, 2025) Computer Anxiety Scale.

All latent constructs were measured using a 7-point Likert scale to enhance statistical granularity and sensitivity (Mumu et al., 2022). This choice is particularly effective for PLS-SEM, as it captures subtle psychological variances in Technophobia and Digital Literacy while improving data distribution normality. To prevent cognitive fatigue among senior respondents, the scale utilized clear verbal anchors and a visually intuitive layout.

To maintain linguistic equivalence, a rigorous back-translation process was conducted by bilingual experts. Finally, a pilot test with 30 participants was performed to refine ambiguous phrasing and ensure high face validity. This meticulous instrument development process ensures that the measurement model is robust enough to precisely assess the "intention-behavior gap" within the silver generation.

4. Data Collection Procedures

Data collection was conducted over a three-month period using a hybrid strategy to mitigate "digital-only" bias and capture a representative spectrum of Technophobia and Digital Literacy. While online surveys were utilized, the majority of data was secured through face-to-face assisted sessions at community centers (Ardyan et al., 2023; Morgan & Harmon, 2001). This physical presence allowed for real-time clarification, reducing cognitive load and ensuring the accuracy of responses regarding Intention to Use and Actual Use.

Rigorous ethical standards were maintained through informed consent and guaranteed anonymity to minimize social desirability bias. To ensure data integrity, a screening process verified age criteria (60+) and exposure to e-government infrastructure. Post-collection, a thorough cleaning phase removed incomplete or "straight-lining" entries. This meticulous protocol ensured that only high-quality data were subjected to the PLS-SEM analysis, bolstering the study's internal validity and the reliability of its findings within the e-government landscape.

5. Data Analysis Technique

Data analysis was executed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4.0. This method was selected for its superior capacity to handle complex structural models involving simultaneous mediation and moderation without requiring strict normality assumptions. As this study aims to reconstruct the UTAUT framework by examining the interaction between Technophobia (TP) and Digital Literacy (DL), the predictive-oriented nature of PLS-SEM provides a robust foundation for theory building and identifying critical success factors in elderly digital adoption (Hair et al., 2024).

The analysis followed a systematic two-stage evaluation approach (Hair et al., 2024a; Memon et al., 2021). The first stage assessed the measurement model (outer model) for reliability and validity using Cronbach's alpha, composite reliability (CR), and the Fornell-Larcker criterion. The second stage evaluated the structural model (inner model) using a non-parametric bootstrapping procedure with 5,000 subsamples to test hypothesized relationships. Moderation effects were estimated via a product-indicator approach, while the "intention-behavior gap" was scrutinized through specific indirect effects analysis.

RESULTS AND DISCUSSION

This section presents the empirical evidence derived from the PLS-SEM analysis, executed through a rigorous two-stage evaluation process. First, the measurement model was assessed to establish the reliability and validity of the latent constructs, ensuring that the indicators for Technophobia, Digital Literacy, and the UTAUT pillars met stringent psychometric criteria. This foundational step guarantees that the data accurately reflects the variables before testing the structural relationships. Subsequently, the structural model was evaluated to examine the hypothesized relationships, focusing on the mediating role of Behavioral Intention and the dual-moderating effects of psychological and cognitive factors on Actual Use.

Assessment of the Measurement Model (Outer Model)

The evaluation of the measurement model is a critical prerequisite for ensuring psychometric integrity within the reconstructed UTAUT framework. Adhering to thresholds by (Hair, Sarstedt, et al., 2019), this assessment establishes internal consistency, convergent validity, and discriminant validity for all constructs, including Technophobia (TP) and Digital Literacy (DL). By verifying outer loadings and Average Variance Extracted (AVE), we confirm that the manifest variables accurately capture the variance of their respective latent constructs.

Reliability was further validated through Cronbach's alpha, rho_A, and Composite Reliability (CR). This rigorous validation mitigates measurement error, ensuring that the subsequent structural analysis of the Intention-to-Use (IU) and Actual Use (AU) relationship is grounded in statistically sound data. This foundational step is essential for precisely identifying the "intention-behavior gap" among older adults.
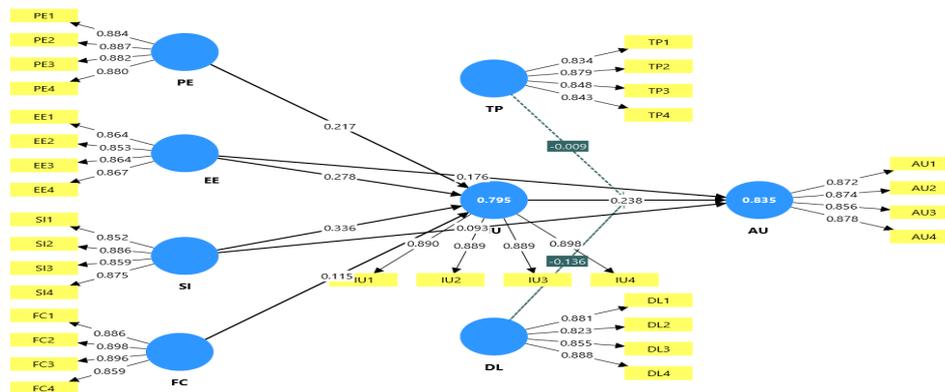
Figure 3. Outer Model

Convergent Validity and Construct Reliability

Convergent validity and construct reliability were evaluated using rigorous psychometric benchmarks to ensure the instrument's stability. Convergent validity was established by confirming that the Average Variance Extracted (AVE) for all constructs exceeded the 0.50 threshold, while indicator outer loadings demonstrated high common variance. Simultaneously, internal consistency was verified through a triad of metrics Cronbach's alpha, rho_A, and Composite Reliability (CR) all surpassing the conservative 0.70 threshold (Hair, Sarstedt, et al., 2019). These results confirm that the latent constructs, including the moderators Digital Literacy and Technophobia, are robustly operationalized. This exceptional psychometric strength mitigates measurement error, providing a reliable foundation for analyzing the complex structural transition from Intention to Use (IU) to Actual Use (AU) in the elderly demographic.

Table 1: Convergent validity and Construct reliability Test Result

Construct	Item	Convergent validity			Construct reliability			
		Loading factors	AVE	Remark	CA	rho_A	CR	Remark
PE	PE1	0,884	0,780	Valid	0,906	0,906	0,934	Reliable
	PE2	0,887						
	PE3	0,882						
	PE4	0,880						
EE	EE1	0,864	0,743	Valid	0,885	0,886	0,920	Reliable
	EE2	0,853						
	EE3	0,864						
	EE4	0,867						
SI	SI1	0,852	0,754	Valid	0,891	0,891	0,924	Reliable
	SI2	0,886						
	SI3	0,859						
	SI4	0,875						
FC	FC1	0,886	0,783	Valid	0,908	0,909	0,935	Reliable
	FC2	0,898						
	FC3	0,896						
	FC4	0,859						
TP	TP1	0,834	0,725	Valid	0,873	0,875	0,913	Reliable
	TP2	0,879						
	TP3	0,848						

Construct	Item	Convergent validity			Construct reliability			
		Loading factors	AVE	Remark	CA	rho_A	CR	Remark
	TP4	0,843						
DL	DL1	0,881	0,743	Valid	0,885	0,889	0,920	Reliable
	DL2	0,823						
	DL3	0,855						
	DL4	0,888						
IU	IU1	0,890	0,794	Valid	0,914	0,914	0,939	Reliable
	IU2	0,889						
	IU3	0,889						
	IU4	0,898						
AU	AU1	0,872	0,757	Valid	0,893	0,894	0,926	Reliable
	AU2	0,874						
	AU3	0,856						
	AU4	0,878						

The empirical results of the measurement model assessment are summarized in Table 1. The analysis reveals that all outer loadings for the respective items of each construct ranged from 0.823 to 0.898, substantially exceeding the recommended threshold of 0.70. This indicates that each indicator possesses a strong individual item reliability. Furthermore, the Average Variance Extracted (AVE) values for all constructs Performance Expectancy (0.780), Effort Expectancy (0.743), Social Influence (0.754), Facilitating Conditions (0.783), Technophobia (0.725), Digital Literacy (0.743), Intention to Use (0.794), and Actual Use (0.757) were well above the requisite 0.50. These results provide robust evidence of convergent validity, confirming that the latent constructs explain more than 50% of the variance of their indicators.

Parallel to the validity testing, the internal consistency reliability of the instrument was confirmed through three rigorous indices. The Cronbach's Alpha (CA) and rho_A values for all constructs exceeded 0.87, while the Composite Reliability (CR) values ranged from 0.913 to 0.939. These figures are significantly higher than the 0.70 benchmark, underscoring the high degree of reliability and stability of the measurement scales across all dimensions. Notably, the mediator (IU) and the moderators (TP and DL) exhibited exceptional psychometric robustness, which is crucial for the subsequent structural testing of the moderation effects. Collectively, these findings validate that the measurement model is psychometrically sound and ready for structural model evaluation.

Discriminant Validity Assessment

To ensure the empirical distinctiveness of the constructs within the reconstructed UTAUT framework, discriminant validity was assessed using the Fornell-Larcker criterion. According to Fornell and Larcker (Radomir & Moisescu, 2020), validity is established when the square root of the Average Variance Extracted (AVE) for each construct exceeds its highest correlation with any other latent variable. This rigorous evaluation is crucial for differentiating overlapping psychological and cognitive constructs, such as Digital Literacy and Technophobia. The results confirm that each construct shares more variance with its own indicators than with other dimensions. Consequently, the model is free from multicollinearity, providing a statistically sound basis for analyzing the structural transition from Intention to Use (IU) to Actual Use (AU) among older adults.

Table 2. The Fornell-Larcker Criterion Test Result

	AU	DL	EE	FC	IU	PE	SI	TP
AU	0,870							
DL	0,852	0,862						
EE	0,843	0,810	0,862					
FC	0,834	0,857	0,842	0,885				
IU	0,851	0,819	0,838	0,827	0,891			
PE	0,830	0,806	0,856	0,859	0,839	0,883		
SI	0,848	0,854	0,827	0,868	0,850	0,852	0,868	
TP	0,845	0,841	0,825	0,846	0,833	0,830	0,858	0,851

The results of the discriminant validity assessment using the Fornell-Larcker criterion are presented in Table 2. To satisfy this criterion, the square root of the Average Variance Extracted (AVE) for each construct represented by the diagonal values in bold must exceed the correlations between that construct and all other latent variables in the model. As evidenced in the table, the square root of the AVE for Actual Use (AU) is 0.870, which is higher than its highest correlation with other constructs (e.g., DL at 0.852). Similarly, Technophobia (TP) exhibits a square root of AVE of 0.851, surpassing its correlation with Digital Literacy (DL) at 0.841 and Social Influence (SI) at 0.858.

All other constructs, including the UTAUT pillars (PE, EE, SI, FC) and the mediator Intention to Use (IU), follow this consistent pattern, where the diagonal values are higher than any off-diagonal correlation coefficients. These findings provide empirical confirmation that each latent variable in the reconstructed model possesses sufficient discriminant validity. Consequently, it can be concluded that each construct represents a distinct theoretical dimension, ensuring that the subsequent structural model analysis, particularly the investigation of the "intention-behavior gap" , is not confounded by multicollinearity or conceptual overlap.

Assessment of the Structural Model (Inner Model)

Following the validation of the measurement model, the structural model was evaluated to examine hypothesized causal relationships and the model's predictive power (Guenther et al., 2023; Hair, Risher, et al., 2019). The assessment involved a systematic procedure, starting with Variance Inflation Factor (VIF) to ensure stable path estimates by excluding multicollinearity. Key metrics including the coefficient of determination (R^2) and effect size (f^2) were analyzed to determine explanatory capability. To test the significance of direct, mediating, and moderating paths, specifically the roles of Technophobia and Digital Literacy, a non-parametric bootstrapping procedure with 5,000 subsamples was employed. This rigorous approach ensures a robust interpretation of the factors bridging the "intention-behavior gap" in inclusive e-government services.
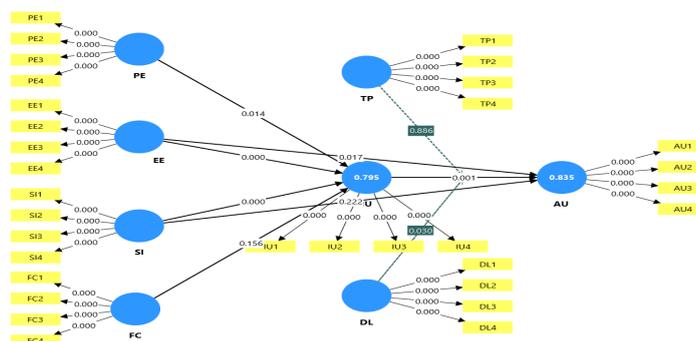
Figure 4. Inner Model

Collinearity Assessment (VIF)

Prior to path evaluation, the model was assessed for multicollinearity to ensure stable, unbiased estimates. Adhering to standards by Hair, Sarstedt, et al., (2019), the Variance Inflation Factor (VIF) was examined for all predictors. While values below 5.0 are acceptable, values below 3.3 are considered ideal, indicating the absence of significant common method bias. The analysis revealed that all VIF values including those for Technophobia and Digital Literacy interaction terms remained consistently below the conservative 3.3 threshold. This confirms the structural model is free from critical collinearity issues, providing a reliable foundation for interpreting hypothesis testing and the complex dynamics of the intention-behavior gap.
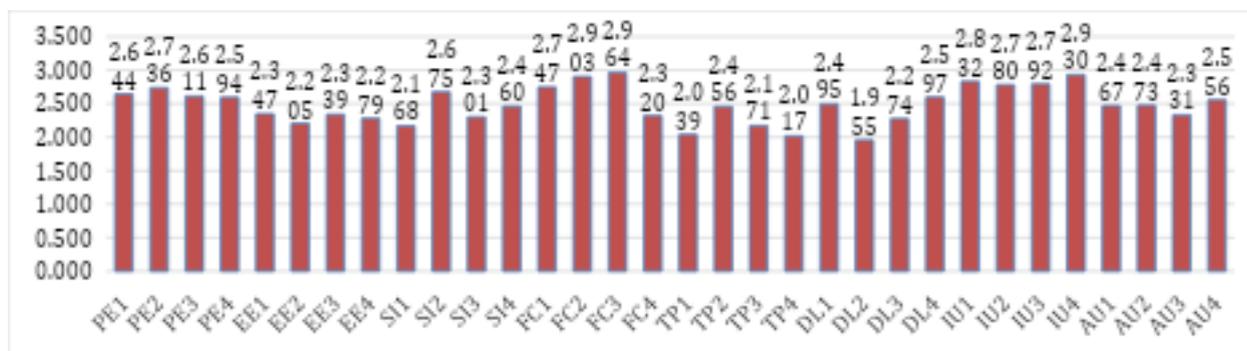

Figure 5. Collinearity Assessment

As shown in Figure 5, the collinearity assessment confirms that all indicators across the latent constructs exhibit Variance Inflation Factor (VIF) values between 1.955 and 2.964. These results fall safely below the conservative threshold of 3.3 recommended by Hair, Sarstedt, et al., (2019). This ensures the absence of pathological collinearity and common method bias, verifying that the indicators for Technophobia (TP), Digital Literacy (DL), and the UTAUT dimensions are empirically distinct. This structural integrity provides a stable and reliable foundation for the subsequent estimation of path coefficients.

Following the confirmation of model stability, the proposed hypotheses were tested by examining path coefficients (β) and their respective significance levels. A non-parametric bootstrapping procedure was utilized to provide a rigorous breakdown of direct and indirect relationships, specifically evaluating how TP and DL influence digital adoption among the elderly. The empirical results, summarized in Table 3, offer a definitive

basis for determining which drivers and moderators significantly bridge the "intention-behavior gap" in the context of inclusive e-government services.

Table 3. Hypothesis Test Result

	Hypothesis	Original Sample (O)	T Statistics	P Values	Decision
H1	PE → IU	0,217	2,448	0,014	Accepted
H2	EE → IU	0,278	3,646	0,000	Accepted
H3	EE → AU	0,176	2,380	0,017	Accepted
H4	SI → IU	0,336	4,129	0,000	Accepted
H5	SI → AU	0,093	1,221	0,222	Not Accepted
H6	FC → IU	0,115	1,417	0,156	Not Accepted
H7	IU → AU	0,238	3,388	0,001	Accepted
H8	TP x IU → AU	-0,009	0,144	0,886	Not Accepted
H9	DL x IU → AU	-0,136	2,165	0,030	Accepted

The structural analysis reveals that Social Influence ($\beta = 0.336$, $p < 0.001$) is the strongest predictor of intention, emphasizing the role of community support in senior digital adoption. Effort Expectancy demonstrates a "dual-impact," significantly influencing both Intention ($\beta = 0.278$, $p < 0.001$) and Actual Use ($\beta = 0.176$, $p = 0.017$), suggesting that perceived ease of use is both a motivational driver and a functional prerequisite. Performance Expectancy also remains a significant driver of intention, confirming that utilitarian value is essential for engagement.

Conversely, Facilitating Conditions failed to predict intention, and Social Influence did not directly impact actual usage, indicating that neither infrastructure nor social pressure alone ensures technical execution. Most notably, Digital Literacy significantly moderates the intention–behavior gap ($\beta = -0.136$, $p = 0.030$), though the negative coefficient suggests a "dampening effect" where increased literacy leads to more selective and critical usage patterns.

Surprisingly, Technophobia did not significantly moderate the path to behavior ($p = 0.886$). This suggests that psychological fear does not necessarily block action once intention is formed, likely because strong social support buffers its inhibitory effects. These interaction results, derived via bootstrapping, provide a robust empirical basis for the reconstructed UTAUT model, clarifying how cognitive competencies rather than psychological fears serve as the primary catalysts in the digital adoption journey of older adults.

Table 4. Mediation Analysis Results

	Hypothesis	Original Sample (O)	T Statistics	P Values	Decision
H7a	PE → IU → AU	0,052	1,845	0,065	Not Accepted
H7b	EE → IU → AU	0,066	2,440	0,015	Accepted
H7c	SI → IU → AU	0,080	2,663	0,008	Accepted

H7d	FC → IU → AU	0,027	1,304	0,192	Not Accepted

The analysis of indirect effects reveals a nuanced role of Behavioral Intention (BI) as a mediator between UTAUT constructs and Actual Use (AU). The findings demonstrate that Effort Expectancy (H7b: β = 0.066, p = 0.015) and Social Influence (H7c: β = 0.080, p = 0.008) exert significant indirect influences on actual usage through the mediation of intention. This suggests that for older adults, the perception of technical ease and the pressure from social circles are powerful enough to transcend the 'intention-behavior gap,' successfully converting psychological willingness into tangible engagement with digital public services. In this context, BI serves as a critical transmission mechanism that channels social support and user-friendliness into sustained adoption behavior.

Conversely, the mediation paths for Performance Expectancy (H7a: p = 0.065) and Facilitating Conditions (H7d: p = 0.192) were found to be non-significant. Although perceived utility (Performance Expectancy) is a known driver of intention, these results indicate that mere awareness of benefits is insufficient to guarantee actual execution among the elderly if not accompanied by practical usability. Similarly, the lack of significant mediation for facilitating conditions reinforces the argument that physical infrastructure acts as a passive prerequisite rather than an active catalyst that moves an individual from intention to action. These findings underscore a vital policy implication: to foster inclusive digital governance, government interventions should prioritize community-based social support and radical system simplification over the mere provision of hardware or general socialization of benefits.

The analysis of these hypotheses facilitated the reconstruction of the UTAUT model. The resulting framework, specifically calibrated for the aging population, is presented in the figure below:
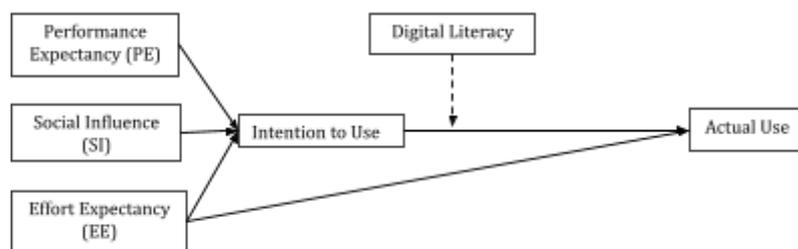

Figure 6. Gerontological Technology Acceptance Model (G-TAM)

Based on the empirical results, the final research model (Figure 6) introduces the Gerontological Technology Acceptance Model (G-TAM), a parsimonious reconstructed UTAUT framework specifically tailored to the elderly demographic. By retaining only the most potent predictors, this model delineates the transition from Intention to Use to Actual Use. Social Influence, Performance Expectancy, and Effort Expectancy emerge as the primary antecedents of intention. Notably, Effort Expectancy exhibits a "dual-impact," influencing both intention and actual behavior directly, underscoring that perceived usability is a fundamental prerequisite for technical execution.

Crucially, the G-TAM bridges the "intention-behavior gap" through the moderating role of Digital Literacy. As illustrated, high motivation alone is insufficient; the translation of intention into action is contingent upon cognitive competence. This architecture confirms

that inclusive digital adoption is driven by social support and usability, but ultimately capitalized by digital literacy as the essential enabler.

Coefficient of Determination (R^2) Test Result

Following the path analysis, the model's predictive power was evaluated using the Coefficient of Determination (R^2) (Kim, 2019). This metric assesses the framework's capacity to explain variance in Behavioral Intention and Actual Use among older adults. By quantifying the collective influence of UTAUT constructs alongside the moderating roles of Technophobia and Digital Literacy, the R^2 values provide empirical evidence of the model's robustness. A high R^2 validates the theoretical integration of psychological and cognitive factors, justifying the reconstructed model's effectiveness in addressing the digital adoption gap.

Table 5. The Coefficient of Determination (R^2) Test Result

	R Square	R Square Adjusted (R^2)
AU	0,835	0,828
IU	0,795	0,790

The assessment of the Coefficient of Determination (R^2) reveals that the reconstructed model possesses substantial predictive power. The R^2 value for Behavioral Intention (IU) is 0.795, indicating that 79.5% of the variance in the intention to use digital public services among older adults is accounted for by the exogenous constructs within the framework. Notably, the Actual Use (AU) variable yields an even higher R^2 of 0.835, signifying that 83.5% of the variance in actual usage behavior is successfully explained by the synergy of the UTAUT pillars and the dual moderators (Technophobia and Digital Literacy). According to the benchmarks established by Hair et al. (2021), these values significantly exceed the 0.75 threshold for substantial explanatory power, thereby validating the structural model's robustness and its superior ability to predict complex digital adoption patterns in the context of inclusive public services.

The Predictive Relevance (Q^2) Test Result

To complement the R^2 assessment, this study performed the Predictive Relevance (Q^2) test using the blindfolding procedure (Sarstedt et al., 2016). While R^2 measures in-sample variance, Q^2 serves as a rigorous indicator of the model's out-of-sample predictive capability. A Q^2 value greater than zero confirms that the exogenous constructs possess significant predictive relevance for Behavioral Intention and Actual Use. These results, presented in Table 6, validate the structural integrity of the reconstructed UTAUT framework and its capacity to accurately predict digital adoption patterns among older adults in broader contexts.

Table 6. The Predictive Relevance (Q^2) Test Result.

	Q^2predict
AU	0,797
IU	0,783

The results of the predictive relevance test yield highly significant Q^2 values for both endogenous constructs. Specifically, Actual Use (AU) achieved a Q^2 value of 0.797, while

Behavioral Intention (IU) recorded a value of 0.783. Since both values are substantially greater than zero and exceed the established threshold of 0.50, the model is confirmed to possess strong predictive relevance (Hair et al., 2021). These findings indicate that the reconstructed UTAUT framework exhibits superior out-of-sample predictive power, demonstrating its robustness in accurately forecasting digital adoption behaviors among older adults. Such high Q^2 scores provide empirical evidence that the structural model is not only statistically sound but also highly effective in capturing the complexities of technology engagement within the context of inclusive public services.

The Effect Size (f^2) Test Result
 To supplement R^2 and Q^2 findings, this study examined Effect Size (f^2) to evaluate the specific contribution of each exogenous construct (Sarstedt et al., 2016). While R^2 measures collective explanatory power, f^2 identifies the practical significance of individual paths by measuring the change in R^2 when a predictor is omitted. In this reconstructed UTAUT framework, the f^2 analysis allows for a granular determination of whether a variable exerts a small (0.02), medium (0.15), or large (0.35) impact on the Behavioral Intention and Actual Use of digital services among older adults. Detailed results are documented in the table below.

Table 7. The Effect Size (f^2) Test Result

	f-square (f^2)	Decision
PE → IU	0,042	Small
EE → IU	0,081	Small
EE → AU	0,040	Small
SI → IU	0,107	Small
SI → AU	0,009	No Effect / Negligible
FC → IU	0,012	No Effect / Negligible
IU → AU	0,067	Small
TP x IU -> AU	0,000	No Effect
DL x IU -> AU	0,027	Small

 The effect size (f^2) analysis reveals the substantive impact of the constructs based on Cohen's (1988) criteria. Despite predominantly small effects, Social Influence (SI → IU) emerged as the strongest practical determinant (f^2 = 0.107), followed by Effort Expectancy, which consistently influenced both intention and actual use. Crucially, the moderating role of Digital Literacy demonstrated practical relevance f^2 = 0.027) in bridging the intention-behavior gap, whereas Technophobia yielded a null effect (f^2 = 0.000), suggesting psychological fear does not substantively inhibit usage once intention is formed. Conversely, Facilitating Conditions and the direct SI → AU path showed negligible effects, confirming that infrastructure and social pressure alone are insufficient to trigger actual behavior without personal intent. These findings prioritize competence-building over anxiety-reduction in fostering digital inclusion for older adults.

Discussion
 The empirical findings confirm that the reconstructed UTAUT model is highly effective in elucidating digital adoption among older adults, with an R^2 for Actual Use reaching 83.5%. Social Influence and Effort Expectancy emerged as the most critical pillars, driving

both intention and behavior. This suggests that for seniors, technology adoption is less a rational utility-based decision and more a social process reliant on community support and system simplification. Consequently, an inclusive digital ecosystem must prioritize trust and interpersonal assistance over mere perceived utility.

A significant theoretical contribution of this research is the contrast between psychological and cognitive factors. While Digital Literacy significantly moderated the intention–behavior gap, Technophobia yielded a negligible effect size (f^2 = 0.000). This challenges long-standing stereotypes by proving that psychological anxiety is no longer the primary deterrent; instead, the lack of technical competence constitutes the true hurdle. Enhancing cognitive capacity and practical skills is therefore more essential for sustained adoption than merely addressing psychological fears.

The mediation of Behavioral Intention clarifies that Performance Expectancy and Facilitating Conditions act as passive prerequisites rather than direct drivers of use. Without adequate literacy, infrastructure alone fails to mobilize seniors. Practically, these results advocate for a policy shift toward community-based digital literacy strategies and high-usability interfaces. By removing competency barriers rather than just socialization efforts, governments can create digital ecosystems that are cognitively accessible and truly inclusive for the aging population.

CONCLUSION

This study successfully reconstructed the UTAUT framework to address digital adoption complexities among older adults, achieving a substantial predictive capacity with an R^2 of 83.5% for actual usage behavior. The findings conclude that Social Influence and Effort Expectancy are the primary drivers of actual use, fully mediated by Behavioral Intention. This underscores that for the "silver generation," the transition to active digital engagement is governed by social support and interface simplicity rather than mere perceived utility.

A pivotal theoretical contribution is the divergent roles of Digital Literacy and Technophobia. While technophobia showed a negligible impact, digital literacy emerged as a critical moderator bridging the intention-behavior gap. This refutes the conventional narrative that psychological anxiety is the main barrier to senior inclusion. Instead, the results posit that technical competence, not psychological fear, is the true gatekeeper of adoption; once intention is formed, execution depends almost entirely on cognitive and practical skills.

Practically, the study provides a strategic roadmap for policymakers to shift from "provision-centric" to "competence-centric" approaches. Interventions should prioritize community-based literacy programs and age-friendly designs to minimize cognitive load. By strengthening social support networks and enhancing digital competence, governments can prevent the digital divide from becoming a permanent barrier to civic engagement, ensuring equitable access to inclusive public services.

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