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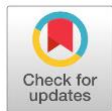
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An Extended TAM Study on QRIS Adoption Among GMIM Youth: Testing the Mediating Roles of Attitude and Behavioral Intention and the Moderating Role of Digital Literacy

Paske V. Modaso¹, Durand Fernandito Freddy Setlight¹, Surya Danang¹

¹Akademi Bisnis dan Keuangan Primaniarta, Indonesia

Article History



Keywords

QRIS, Technology Acceptance Model, Continuance Intention, Digital Literacy, PLS-SEM

JEL Classification

G21, M31, D91, O33, Z13

Abstract

This study investigates the continued adoption of the Quick Response Code Indonesian Standard (QRIS) among youth members of the Evangelical Christian Church in Minahasa (GMIM) by extending the Technology Acceptance Model (TAM). The research framework integrates attitude and behavioral intention as sequential mediators, alongside digital literacy as a moderator influencing the relationship between perceived usefulness and attitude. Employing a quantitative cross-sectional design, data were collected from 150 purposively selected young users aged 17–30 years and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings demonstrate that perceived ease of use significantly drives both perceived usefulness and user attitude, which subsequently predict behavioral intention and long-term continuance intention. Furthermore, a serial mediation pathway from ease of use through perceptions, attitudes, and intentions to continuance intention is confirmed. Crucially, digital literacy serves as a vital boundary condition: perceived usefulness strongly shapes user attitudes among individuals with high digital literacy, whereas this effect is insignificant among those with low digital literacy. Overall, the results highlight that sustained digital payment adoption operates through a structured psychological sequence contingent on users' digital competencies.

Introduction

Digital payment ecosystems have fundamentally reshaped modern financial interactions, with platforms like the Quick Response Code Indonesian Standard driving unprecedented transaction efficiency. Yet achieving high initial adoption rates solves only half the puzzle. The enduring challenge for financial technology providers lies in preventing user attrition after the initial novelty fades. Younger users are particularly prone to this volatility. They often adopt new applications rapidly but abandon them just as quickly if the operational experience fails to confirm their expectations or if shifting daily routines disrupt their usage patterns (Bhattacharjee, 2001; Limayem et al., 2007). Maintaining continuous usage requires more than

¹Corresponding Author: Paske V. Modaso, Email: paskevictorymodaso@gmail.com, Address: Jl. A.A. Maramis No.273, Paniki Satu, Kec. Mapanget, Kota Manado, Sulawesi Utara 95259

a functional platform; it demands ongoing trust transfer (Cao et al., 2018) and a user base capable of seamlessly integrating the technology into their daily lives.

While researchers heavily rely on the Technology Acceptance Model (Davis, 1989; Davis et al., 1989) to decode user behavior, modern applications of this theory often strip away its most vital psychological components. A troubling pattern in recent information systems literature is the tendency to draw direct theoretical lines from cognitive beliefs to behavioral intention, bypassing the user attitude construct entirely (Marangunić & Granić, 2015). This structural shortcut creates a severe diagnostic blind spot. When researchers ignore the affective evaluation stage, they cannot determine if users abandon an application because they failed to develop a positive emotional disposition toward it or if they simply failed to translate that positive feeling into actual behavioral commitment. Restoring the full sequence from cognition to affection to conation is absolutely essential for understanding why users commit to prolonged technology use.

Beyond these structural omissions, prevailing adoption frameworks also tend to treat user capability as a constant. This assumption ignores the widening second level digital divide, where inequality is defined not by physical access to devices but by the operational skills required to use them effectively (Van Deursen & Van Dijk, 2019). Two individuals might both recognize that mobile payments offer significant practical value (Oliveira et al., 2016). However, their ability to realize that value diverges sharply based on their capacity to navigate interface features, assess security protocols, and independently resolve technical errors. Therefore, digital literacy is not merely a basic precursor to perceived ease of use. It serves as a critical boundary condition that determines whether a user can successfully convert the recognized utility of a system into a genuinely positive attitude.

This study addresses these theoretical deficiencies by analyzing the continuance intention of a highly active community, specifically the youth members of the Evangelical Christian Church in Minahasa. Prior baseline research confirms that fundamental technological perceptions influence initial adoption within this exact demographic (Modaso & Barek, 2025), yet the mechanisms sustaining their enduring engagement require deeper investigation. By developing a comprehensive framework that restores both attitude and behavioral intention as sequential mediators, this research maps the complete psychological journey of the user. Crucially, by positioning digital literacy as a moderating force between perceived usefulness and attitude, this paper offers a explanation of how individual operational capabilities dictate the translation of perceived value into lasting behavioral commitment.

Literature Review

Technology Acceptance Model (TAM)

This study is grounded in the Technology Acceptance Model (TAM) developed by Davis (1989), which posits that an individual's acceptance of a technology is largely determined by two core beliefs: Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). These two beliefs shape the Attitude Toward Using (ATU), which subsequently forms the Behavioral Intention (BI), before finally manifesting as actual usage behavior. This causal chain perception, attitude, intention, and behavior serve as the study's fundamental framework for explaining the adoption and continued use of QRIS.

TAM does not stand alone. It shares theoretical roots with Ajzen's (1991) Theory of Planned Behavior (TPB), which asserts that behavioral intention is shaped by evaluative beliefs regarding a specific action. Meanwhile, the Unified Theory of Acceptance and Use of

Technology (UTAUT) proposed by Venkatesh et al. (2003) integrates eight earlier technology acceptance models including TAM and TPB into a more comprehensive construct. These two theories are employed not as primary models, but to reinforce the argument that the psychological mechanism of perception-attitude-intention the core of TAM has proven relevant across various contexts of technology acceptance, including digital payment systems.

Perceived Ease of Use (PEOU)

Perceived Ease of Use refers to an individual's perception regarding the level of ease involved in understanding and using a technology. Davis (1989) defines it as the degree of belief that using a particular system will be free of significant effort. In the context of QRIS, PEOU describes the extent to which users view the QRIS payment process as easy to learn, understand, and operate, without requiring excessive effort.

Ease of use has two significant consequences. First, a technology that is easy to use can directly lead to a more positive evaluation of that technology. Secondly, ease of use can enhance the perception of a technology's usefulness, as greater ease of use allows users to more readily derive benefits from that technology. Davis (1989) identified a significant relationship between PEOU and PU. Conceptually, the easier a system is to use, the more likely users are to perceive it as useful. In the context of QRIS research, this relationship is relevant because QRIS does not operate as a standalone application but rather functions as part of a broader payment or digital banking application ecosystem. User experiences involving code scanning, transaction confirmation, verification, and settlement processes can influence the overall perception of ease of use. Consequently, in this study, PEOU is positioned as an exogenous construct that influences both PU and ATU.

Perceived Usefulness (PU)

Perceived Usefulness (PU) refers to a user's perception of the extent to which a technology provides benefits in supporting their activities. Davis (1989) defines PU as the degree of belief that using a specific system will enhance performance. In the context of QRIS, PU can be understood as the perception that QRIS offers benefits for payment activities such as making transactions more practical, accelerating the payment process, facilitating ease of transaction, and helping users make payments more effectively.

PU is a central construct of the Technology Acceptance Model (TAM) because individuals tend to accept a technology if they perceive it as providing tangible benefits. In the context of mobile payments, Oliveira et al. (2016) demonstrated that perceived benefits constitute a crucial factor in the acceptance of payment technology. Research on technology adoption in developing countries also indicates that TAM constructs, including PU, remain relevant for explaining behavioral intention. In this study, PU holds a strategic position; it is not only predicted by Perceived Ease of Use (PEOU) but also serves as a predictor of Attitude Toward Using (ATU), while simultaneously acting as a construct whose influence on ATU is tested through the moderating role of digital literacy.

Attitude Toward Using (ATU)

Davis et al. (1989) define Attitude Toward Using (ATU) as an individual's overall affective evaluation encompassing both positive and negative feelings regarding the act of using a system. In the original TAM, ATU acts as a mediator bridging cognitive beliefs (PEOU and PU) and behavioral intention (BI). However, as highlighted by Marangunić & Granić (2015) in their review of nearly three decades of TAM literature, many contemporary studies omit ATU, linking PEOU and PU directly to BI instead. This simplification risks obscuring the diagnosis of the actual issue: whether adoption failure stems from a failure to form a positive

attitude, or from a failure to convert that positive attitude into a strong intention. Consequently, this study reinstates ATU as an explicit mediator within the model. Behavioral Intention (BI)

Behavioral Intention represents a measure of the strength of an individual's intention to perform a specific behavior in this case, the intention to use QRIS. Rooted in the Theory of Reasoned Action tradition which also underpins the Theory of Planned Behavior (Ajzen, 1991) BI is positioned within the TAM framework as a direct consequence of Attitude Toward Use (ATU) and, simultaneously, as the immediate predictor of actual usage behavior. BI serves as a crucial element in this model because it bridges the established attitude with the behavioral continuity that constitutes the study's ultimate focus.

Continuance Intention (CI)

Most technology acceptance studies stop at Behavioral Intention (BI) as the final dependent variable; however, initial usage intention is not synonymous with the intention to continue using the technology consistently post-adoption. Bhattacharjee (2001), through the Expectation-Confirmation Model (ECM), asserts that continuance behavior is conceptually distinct from initial adoption behavior, as it is shaped by expectation confirmation and user satisfaction following actual usage experience rather than merely by intentions formed prior to use. Cao et al. (2018) reinforce the relevance of this concept in the context of mobile payments, demonstrating how trust transfer mechanisms influence the intention to continue usage. Meanwhile, Limayem et al. (2007) show that habit can limit the predictive power of intention regarding sustained usage over time a finding that underscores the importance of measuring Continuance Intention (CI) as a distinct construct, rather than simply assuming it automatically follows BI. On this basis, the present study extends the model's outcome to CI, rather than stopping at BI.

Digital Literacy (DL)

Van Deursen and Van Dijk (2019) argue that the digital divide has shifted: it is no longer solely a matter of physical access to devices and networks (first-level divide), but rather a question of an individual's capacity and ability to utilize technology effectively (second-level divide). In this study, Digital Literacy refers to that capacity. Unlike most studies that position digital literacy as a direct antecedent of Perceived Ease of Use (PEOU) or Perceived Usefulness (PU), this study positions it as a moderator of the PU→ATU (Attitude Toward Use) path. The argument is that two individuals who both perceive QRIS as beneficial may differ in the extent to which that perception is truly internalized into a positive attitude, depending on their digital capacity to evaluate and operate the application and to overcome technical obstacles associated with it

Methods

This study employs a quantitative approach with a cross-sectional survey design, involving data collection at a single point in time via a self-report instrument. This design was selected because the research objective is explanatory specifically, to test causal relationships among latent constructs derived from the Technology Acceptance Model and its extensions rather than to describe a phenomenon or develop a new theory. A consequence of the cross-sectional design is that the "Continuance Intention" construct represents the intention to continue usage rather than actual continued behavior; this limitation is explicitly addressed in the limitations section.

The study population consists of GMIM (Evangelical Christian Church in Minahasa) youth aged 17 to 30 who have used or are currently using QRIS as a payment method. A complete

sampling frame was unavailable due to the dynamic nature of church youth membership; consequently, probability sampling techniques could not be applied.

Sampling was conducted using a purposive sampling technique based on three inclusion criteria: (1) aged 17–30 years; (2) status as a GMIM youth member; and (3) past or current use of QRIS. The second and third criteria were operationalized as screening questions at the beginning of the questionnaire, with instructions for respondents who did not meet them to discontinue the survey. Thus, it was ensured that all respondents included in the analysis met all three criteria. The final sample analyzed comprised 150 respondents.

Sample Size Justification

The determination of the minimum sample size was based on the inverse square root method developed by Kock and Hadaya (2018). This method was chosen because the previously common "ten-times rule" tends to yield imprecise estimates. With a sample size of 150 respondents, the model is capable of detecting path coefficients of 0.203 or greater at the required level of statistical power. For comparison, the "ten-times rule" criterion requires a minimum of 40 respondents, given that the maximum number of arrows pointing to a single construct in the model is four specifically for the *Attitude Toward Using* construct. Consequently, the sample size employed satisfies both criteria for all main paths in the model. It should be noted that the interaction path $LD \times PU \rightarrow ATU$ has a coefficient of 0.198, which is marginally below that detection threshold; the implications of this for statistical power are discussed in the results and limitations sections.

Operationalization of Variables and Instruments

This study involves six latent constructs, all specified reflectively and each measured by four indicators, resulting in a total instrument comprising 24 items. All items were adapted from validated instruments found in the literature and contextualized for the use of QRIS.

Table 1. Operationalization of Research Variables

Construct	Operational Definition	Code
<i>Perceived Ease of Use</i> (PEOU)	An individual's perception regarding the ease of learning and operating QRIS without significant effort	PEOU1–PEOU4
<i>Perceived Usefulness</i> (PU)	An individual's perception regarding the extent to which using QRIS enhances the speed and efficiency of their transactions	PU1–PU4
<i>Attitude Toward Using</i> (ATU)	An individual's overall affective evaluation whether positive or negative of using QRIS	ATU1–ATU4
<i>Behavioral Intention</i> (BI)	The strength of an individual's intention to use QRIS for future financial transactions	BI1–BI4
<i>Continuance Intention</i> (CI)	An individual's intention to consistently maintain the use of QRIS over the long term	CI1–CI4
Digital Literacy (LD)	An individual's capacity to operate features, recognize security risks, obtain information, and resolve technical issues related to QRIS	LD1–LD4

All indicators were measured using a five-point Likert scale, with anchors of 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly Agree.

Data Collection Procedure

The questionnaire was structured into two sections. Section A covered respondent characteristics and two screening questions, while Section B contained 24 research statement items. The introduction to the questionnaire included the researcher's and institution's identities, the research objective, a statement indicating there were no right or wrong answers, and a guarantee of data confidentiality and its exclusive use for scientific purposes.

Participation was voluntary, and respondents could provide only their initials, thereby preserving anonymity. Prior to analysis, the data were examined to ensure suitability. None of the 150 cases contained missing values, and all responses fell within the valid scale range of 1 to 5. An examination of response patterns revealed that only one respondent provided identical answers for all items; thus, indications of straight-lining were minimal, and no case elimination was required.

Given that the data were derived from a single source and collected via a self-report instrument at a single point in time, the potential for common method bias was managed using two approaches recommended by Podsakoff et al. (2003). Procedurally, respondent anonymity was guaranteed; a statement noting the absence of right or wrong answers was included to reduce the tendency toward normative responding; and instrument items were formulated to be concise and unambiguous. Statistically, a full collinearity assessment was conducted following Kock's (2015) procedure, requiring all Variance Inflation Factor (VIF) values in the structural model to remain below 3.30.

Data Analysis Technique

Data analysis was performed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with the aid of SmartPLS 4 software (Ringle et al., 2024). The PLS-SEM approach was selected based on three considerations: the research model is complex, featuring a sequential mediation chain and a single moderation effect; the analysis objective is oriented toward prediction and theory development rather than the confirmation of established theories; ...and the sample size is relatively moderate, making covariance-based estimation less suitable (Hair et al., 2019). The analysis was conducted in two stages following standard procedures. The first stage evaluated the measurement model through indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. The second stage evaluated the structural model by examining collinearity, path coefficient significance, the coefficient of determination, effect size, and predictive relevance.

The moderating effect of Digital Literacy on the PU → ATU path was estimated using the two-stage approach (Henseler & Chin, 2010), which offers higher statistical power than the product-indicator approach for models involving reflective constructs. The moderator's main effect on the dependent variable was also included in the model as a prerequisite for interpreting the interaction coefficient. The nature of the moderation was further examined through simple slope analysis at three levels of the moderator: one standard deviation above the mean, the mean, and one standard deviation below the mean. The significance of all coefficients was determined using a bootstrapping procedure with 5,000 subsamples and a bias-corrected and accelerated confidence interval scheme. Mediation effects were tested via specific indirect effect analysis, following the approaches of Preacher and Hayes (2008) and Zhao et al. (2010). The model's predictive relevance was evaluated using the PLSpredict procedure with ten-fold cross-validation and ten repetitions (Shmueli et al., 2019), complemented by the Cross-Validated Predictive Ability Test (Liengaard et al., 2021).

Results and Discussion

Table 2 shows that the respondent profile is dominated by the 21–25 age group (48.00%), followed by the 17–20 age group (28.67%) and the 26–30 age group (23.33%). This composition places the majority of respondents at a young age bracket that is relatively familiar with digital technology and app-based transactions. Regarding gender, the composition is relatively balanced, although females are slightly more dominant (52.00%) than males (48.00%).

In terms of education level, the respondents are predominantly bachelor's degree holders (59.33%), while 32.67% have a high school or vocational high school (SMA/SMK) education. This composition indicates that most respondents possess a secondary to tertiary educational background, which is relevant to the research context, as the Extended TAM model identifies the ability to understand and operate technology as a crucial factor in shaping perceptions and attitudes toward QRIS. Regarding occupation, university students constitute the largest group (52.00%), followed by entrepreneurs (20.67%) and private-sector or contract employees (18.00%). Meanwhile, QRIS usage is quite intensive; 36.67% of respondents use it 3–5 times per week, and 29.33% use it more than five times per week. This pattern indicates that the majority of respondents have relatively routine experience using QRIS; consequently, their assessments of ease of use, usefulness, attitude, intention to use, and intention to continue using are based on actual usage experience rather than merely on perceptions of the technology.

The most dominant transaction types are Food & Beverages (38.00%) and daily necessities (27.33%), while donations or church offerings account for 11.33%. Overall, the profile reveals a sample dominated by young users with fairly routine QRIS experience in their daily transactions. This characteristic aligns with the research context, which examines the perception–attitude–intention–continuance intention mechanism, as well as the role of digital literacy in determining the extent to which perceived benefits translate into a positive attitude toward QRIS

Table 2. Respondent demographics

Characteristics	Category	Frequency (n)	Percentage (%)
Age	17–20 years	43	28.67
	21–25 years	72	48.00
	26–30 years	35	23.33
	Total	150	100.00
Gender	Male	72	48.00
	Female	78	52.00
	Total	150	100.00
Last Education	S2/S3 (Master's/Doctoral)	5	3.33
	S1 (Bachelor's)	89	59.33
	D1–D3 (Diploma)	7	4.67
	Senior High School (SMA/SMK)	49	32.67
	Total	150	100.00
Occupation	ASN / Civil Servant	7	4.67
	BUMN/D	6	4.00
	Private / Honorary	27	18.00
	Self-employed	31	20.67
	Student	78	52.00
	Other	1	0.66
	Total	150	100.00
Frequency of QRIS Use	More than 5 times/week	44	29.33
	3–5 times/week	55	36.67
	1–2 times/week	37	24.67
	Less than 4 times/month	14	9.33
	Total	150	100.00
Most Frequent Transaction Type	Daily necessities	41	27.33
	Food & Beverages	57	38.00
	Church donations/offering	17	11.33
	Bills & utilities	17	11.33
	Other	18	12.00

Total	150	100.00
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Indicator Reliability and Convergent Validity (Outer Model)

Indicator reliability is assessed via outer loading values, with a minimum threshold of 0.708, indicating that the construct explains more than 50% of the variance of its indicators (Hair et al., 2019).

Table 3. Outer Loading Test Results

Construct	Indicator	Outer Loading	Std. Deviation	t-statistic	p-value	Note
<i>Perceived Ease of Use</i> (PEOU)	PEOU1	0,854	0,025	34,525	0,000	Valid
	PEOU2	0,883	0,021	42,575	0,000	Valid
	PEOU3	0,862	0,027	32,199	0,000	Valid
	PEOU4	0,845	0,027	30,903	0,000	Valid
<i>Perceived Usefulness</i> (PU)	PU1	0,871	0,027	32,593	0,000	Valid
	PU2	0,857	0,027	32,137	0,000	Valid
	PU3	0,860	0,028	30,912	0,000	Valid
	PU4	0,866	0,026	33,045	0,000	Valid
<i>Attitude Toward Using</i> (ATU)	ATU1	0,817	0,034	24,241	0,000	Valid
	ATU2	0,851	0,033	25,994	0,000	Valid
	ATU3	0,825	0,029	28,890	0,000	Valid
	ATU4	0,847	0,028	30,374	0,000	Valid
<i>Behavioral Intention</i> (BI)	BI1	0,849	0,025	34,391	0,000	Valid
	BI2	0,883	0,022	40,541	0,000	Valid
	BI3	0,868	0,022	39,973	0,000	Valid
	BI4	0,894	0,019	47,802	0,000	Valid
<i>Continuance Intention</i> (CI)	CI1	0,868	0,023	38,207	0,000	Valid
	CI2	0,871	0,023	37,435	0,000	Valid
	CI3	0,876	0,027	32,961	0,000	Valid
	CI4	0,867	0,028	31,117	0,000	Valid
Digital Literacy (LD)	LD1	0,817	0,069	11,912	0,000	Valid
	LD2	0,867	0,074	11,706	0,000	Valid
	LD3	0,842	0,076	11,128	0,000	Valid
	LD4	0,787	0,087	9,063	0,000	Valid

All 24 indicators have outer loading values above 0.708, with a range of 0.787 (LD4) to 0.894 (BI4), and all are significant at the 1% level based on a bootstrapping procedure with 5,000 subsamples. Thus, there are no indicators that need to be eliminated from the model. The distribution pattern of loading values provides information that goes beyond simply meeting a statistical threshold. The Behavioral Intention construct shows the highest homogeneity (range 0.849–0.894), which indicates that the four indicators of behavioral intention are interpreted by respondents as manifestations of a very coherent meaning domain. In contrast, the Digital Literacy construct shows the lowest estimation precision, reflected in the bootstrap standard deviation value which ranges between 0.069–0.087 around three times higher than other constructs which range from 0.019–0.034 as well as the lowest t-statistic value in the model (LD4, $t = 9.063$). This finding is consistent with Van Deursen and Van Dijk's (2019) argument that digital literacy is essentially a multidimensional construct that includes operational, informational and strategic skills. Operationalization as a single reflective construct, as adopted in this research, still meets all measurement feasibility criteria, but comes with consequences in the form of higher estimate variability.

Internal Consistency Reliability and Average Variance Extracted (AVE)

Internal consistency reliability is evaluated through three coefficients: Cronbach's alpha as a conservative lower bound, composite reliability ρ_c as a liberal upper bound, and ρ_a

(Dijkstra & Henseler, 2015) as a compromise estimator that generally falls between the two. Convergent validity at the construct level is assessed through Average Variance Extracted (AVE) with a minimum threshold of 0.50.

Table 4. Results of Reliability Test and Convergent Validity of Constructs

Construct	Cronbach's Alpha	rho_a	Composite Reliability	AVE	Information
<i>Perceived Ease of Use</i> (PEOU)	0,884	0,887	0,920	0,741	Reliable and Valid
<i>Perceived Usefulness</i> (PU)	0,886	0,887	0,921	0,746	Reliable and Valid
<i>Attitude Toward Using</i> (ATU)	0,855	0,858	0,902	0,697	Reliable and Valid
<i>Behavioral Intention</i> (BI)	0,896	0,897	0,928	0,763	Reliable and Valid
<i>Continuance Intention</i> (CI)	0,894	0,898	0,926	0,758	Reliable and Valid
Digital Literacy (LD)	0,849	0,864	0,897	0,686	Reliable and Valid

All constructs met reliability criteria, with Cronbach's alpha values ranging from 0.849 to 0.896 and composite reliability values ranging from 0.897 to 0.928. For each construct, the rho_a value consistently fell between Cronbach's alpha and rho_c, aligning with theoretical expectations and indicating a stable reliability estimate independent of the specific coefficient chosen. It should be noted that all composite reliability values remained below 0.95. Hair et al. (2019) warn that reliability values exceeding this threshold may indicate semantic redundancy among indicators a condition where instrument items essentially ask the same question using different wording, thereby artificially inflating reliability estimates without adding measurement information. The reliability values in this study fell within the optimal range: high enough to ensure consistency, yet free from signs of item redundancy. The AVE values for all constructs ranged from 0.686 (LD) to 0.763 (BI), all exceeding the 0.50 threshold. This indicates that each construct explains at least 68.6% of the variance in its indicators, thereby satisfying convergent validity by a substantial margin.

Discriminant Validity

Discriminant validity assesses the extent to which a construct is empirically distinct from other constructs in the model. This assessment is conducted using three complementary approaches: the Heterotrait Monotrait (HTMT) ratio, the Fornell-Larcker criterion, and cross-loading analysis.

Table 5. Heterotrait-Monotrait Ratio (HTMT)

	ATU	BI	CI	LD	PEOU	PU
ATU						
BI	0,617					
CI	0,664	0,617				
LD	0,357	0,620	0,529			
PEOU	0,765	0,682	0,650	0,374		
PU	0,615	0,720	0,658	0,542	0,684	

Henseler et al. (2015) recommend a threshold of 0.90 for conceptually close constructs and a more conservative threshold of 0.85 for conceptually distinct constructs. All HTMT values in this study fell below 0.85, with the highest value being 0.765 for the PEOU–ATU pair. The relative closeness of these two constructs is theoretically understandable, given that TAM positions perceived ease of use as a direct determinant of attitude formation; however, the value

of 0.765 remains sufficiently distant from the conservative threshold, indicating no issues regarding discriminant validity.

The most significant finding to highlight is the HTMT value of 0.617 for the BI–CI pair. Testing this pair is crucial because Behavioral Intention and Continuance Intention are both intention-based constructs; thus, they are *a priori* susceptible to conceptual overlap a risk that often serves as a primary objection to models positioning the two sequentially. The value of 0.617 demonstrates that respondents empirically distinguish between the intention to use and the intention to continue use as two distinct psychological orientations. This finding provides empirical support for Bhattacharjee's (2001) conceptualization which positions continuance intention as a post-adoption outcome analytically separate from pre-adoption intention while also justifying the extension of the TAM model to the continuance stage, as proposed in this study.

Table 6. Fornell-Larcker Criterion

	ATU	BI	CI	LD	PEOU	PU
ATU	0,835					
BI	0,547	0,873				
CI	0,582	0,556	0,871			
LD	0,313	0,545	0,470	0,829		
PEOU	0,668	0,609	0,579	0,332	0,861	
PU	0,539	0,643	0,586	0,470	0,609	0,863

The Fornell-Larcker criterion (1981) requires that the square root of the AVE for each construct exceeds its correlation with any other construct. This requirement is met for all constructs. For instance, the square root of the AVE for ATU (0.835) exceeds its highest correlation 0.668 with PEOU while the square root of the AVE for LD (0.829) exceeds its highest correlation 0.545 with BI. Cross-loading analysis, serving as the third criterion, demonstrates that each indicator loads most strongly on its intended construct compared to all other constructs in the model. The smallest difference between the loading on the parent construct and the highest cross-loading was 0.257 (indicator ATU3 against PEOU), a substantially adequate margin. The convergence of results from these three approaches reinforces the conclusion that the six constructs in the model represent distinct empirical concepts.

Indicator Collinearity and Indications of Common Method Bias

Collinearity testing within the measurement model reveals indicator Variance Inflation Factor (VIF) values ranging from 1.764 (LD4) to 2.858 (BI4). All values fall below the critical threshold of 5.00 and even the conservative threshold of 3.30; thus, there is no indication of collinearity that would compromise the estimation of indicator weights. Given that the research data were collected from a single source via a self-report instrument at a single point in time, the potential for common method bias (CMB) warrants special attention. Based on the full collinearity assessment approach developed by Kock (2015), VIF values in the structural model range from 1.000 to 1.975, all falling below the 3.30 threshold. These results indicate that common method variance does not pose a serious threat to the validity of the findings, although it should be noted that this procedure is a diagnostic approach rather than a definitive test for CMB. Overall, the measurement model in this study meets all evaluation criteria required for reflective constructs. All indicators demonstrate adequate reliability, the six constructs exhibit high internal consistency without signs of item redundancy, convergent validity is achieved by a substantial margin, and discriminant validity is consistently confirmed through three distinct approaches. Notably, the empirical distinction between Behavioral Intention and Continuance Intention provides a robust measurement foundation for testing a structural model that extends

the TAM framework to the stage of continued usage. With all these criteria satisfied, the analysis can proceed to the structural model evaluation stage.

Structural Model Evaluation (Inner Model)

Once the measurement model was confirmed to meet all adequacy criteria, the analysis proceeded to the evaluation of the structural model to examine the causal relationships between latent constructs. Following the procedures recommended by Hair et al. (2019), the evaluation was conducted in five stages: examining collinearity among predictor constructs, testing path coefficient significance, assessing the coefficient of determination (R^2), evaluating effect size (f^2), and assessing the model's predictive relevance. The significance of all coefficients was determined via a bootstrapping procedure with 5,000 subsamples, utilizing a bias-corrected and accelerated confidence interval scheme.

Structural Model Collinearity Test

Before interpreting the path coefficients, it was necessary to ensure that collinearity among predictor constructs did not interfere with the estimation. The Variance Inflation Factor (VIF) values in the structural model ranged from 1.000 to 1.975; the highest value was observed for the PU $\rightarrow$ ATU path (VIF = 1.975), followed by LD $\rightarrow$ ATU (1.799) and LD $\times$ PU $\rightarrow$ ATU (1.779). All values fell well below the critical threshold of 3.30 (Kock, 2015) and the conventional threshold of 5.00, indicating that the path coefficient estimates were not distorted by collinearity among predictors. It should be noted that the VIF value for the endogenous construct ATU was relatively higher than those of other paths because the construct received four simultaneous predictors; however, the magnitude remained within a safe range.

Direct Effect Hypothesis Testing

Table 7. Direct Effect Hypothesis Testing Results

Hypothesis	Track	Coef	Std. Dev	t	p	BCa CI 95%	Decision
H1	PEOU $\rightarrow$ PU	0,609	0,085	7,172	0,000	[0,410; 0,749]	Accepted
H2	PEOU $\rightarrow$ ATU	0,482	0,099	4,847	0,000	[0,277; 0,664]	Accepted
H3	PU $\rightarrow$ ATU	0,301	0,094	3,207	0,001	[0,126; 0,494]	Accepted
H4	ATU $\rightarrow$ BI	0,547	0,094	5,840	0,000	[0,335; 0,707]	Accepted
H5	BI $\rightarrow$ CI	0,556	0,088	6,305	0,000	[0,355; 0,712]	Accepted
LD $\rightarrow$ ATU (main effect)		0,247	0,103	2,408	0,016	[0,058; 0,455]	Significant

All hypotheses regarding direct effects were statistically confirmed. The 95% confidence intervals for each path excluded zero, reinforcing the conclusion of significance without relying solely on p-values. The PEOU $\rightarrow$ PU path exhibited the largest coefficient in the model ($\beta = 0.609$), confirming that perceived ease of use is a primary determinant in the formation of perceived usefulness regarding QRIS. Regarding the ATU construct, perceived ease of use also made a greater direct contribution ($\beta = 0.482$) than perceived usefulness ($\beta = 0.301$). This pattern of PEOU dominance is consistent with findings from previous research on the same population (Modaso & Barek, 2025), indicating that in the context of low-value, high-frequency transactions, operational ease is a stronger driver of user response than considerations of utility.

In the latter part of the model, the coefficients for ATU $\rightarrow$ BI ($\beta = 0.547$) and BI $\rightarrow$ CI ($\beta = 0.556$) were of nearly equal magnitude. This parity indicates that the transitions from attitude to intention and from intention to continuance intention occur with comparable intensity, with no single stage acting as a conspicuous weak link in the psychological chain of technology acceptance. The main effect of Digital Literacy on ATU was also found to be significant ($\beta =$

0.247; $p = 0.016$). This finding demonstrates that digital capability does not merely function as a contextual condition but also directly shapes attitudes toward QRIS.

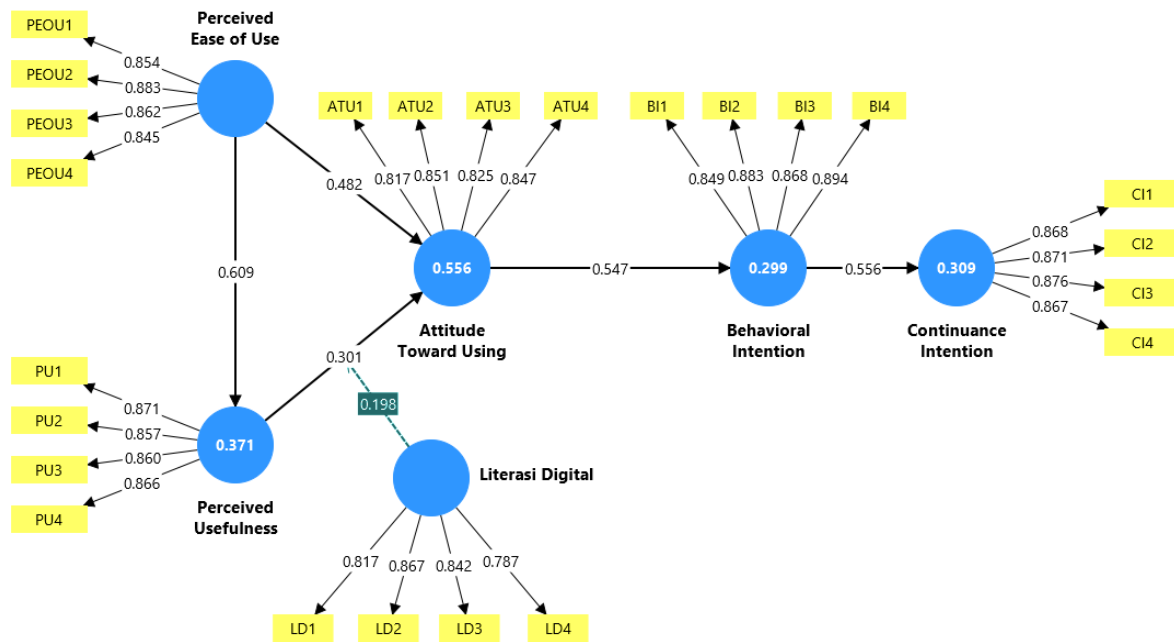


Figure 1. Structural model

Mediation Effect Testing

The mediation effect was tested through an analysis of specific indirect effects using the bootstrapping procedure, in accordance with the approaches recommended by Preacher and Hayes (2008) and Zhao et al. (2010).

Table 8. Mediation Effect Test Results (Specific Indirect Effects)

Mediation Process	Coefficient (O)	Std. Deviation	t-statistic	p-value	Information
ATU → BI → CI	0,304	0,081	3,769	0,000	Significant
PEOU → ATU → BI	0,263	0,073	3,594	0,000	Significant
PEOU → PU → ATU	0,183	0,068	2,717	0,007	Significant
PU → ATU → BI	0,165	0,059	2,787	0,005	Significant
PEOU → ATU → BI → CI	0,146	0,051	2,854	0,004	Significant
LD → ATU → BI	0,135	0,065	2,092	0,036	Significant
LD × PU → ATU → BI	0,108	0,039	2,799	0,005	Significant
PEOU → PU → ATU → BI	0,100	0,041	2,458	0,014	Significant
PU → ATU → BI → CI	0,092	0,038	2,382	0,017	Significant
LD → ATU → BI → CI	0,075	0,040	1,858	0,063	Not Significant
LD × PU → ATU → BI → CI	0,060	0,026	2,346	0,019	Significant
PEOU → PU → ATU → BI → CI	0,056	0,026	2,163	0,031	Significant

The sixth hypothesis (H6), stating that ATU and BI mediate the influence of PEOU and PU on CI, was confirmed. Eleven of the twelve identified indirect paths proved significant at the 5% level. A noteworthy finding is the sustained significance of the five-stage serial mediation path: PEOU → PU → ATU → BI → CI ($\beta = 0.056$; $p = 0.031$). Serial indirect effects result from the product of coefficients across stages; consequently, long chains mathematically undergo progressive attenuation and tend to lose significance. The persistence of this path demonstrates that the psychological mechanisms postulated by the original TAM—spanning from perception, through attitude and intention, to continued usage—operate intact as a coherent sequence rather than as fragmented, isolated relationships.

The only path that failed to reach significance was $LD \rightarrow ATU \rightarrow BI \rightarrow CI$ ($\beta = 0.075$; $p = 0.063$). This result indicates that the influence of digital literacy on continuance intention is not adequately transmitted through the attitude-intention chain, even though its influence on BI via ATU was significant ($\beta = 0.135$; $p = 0.036$). In other words, the contribution of digital literacy tends to diminish as it traverses the entire chain leading to the continuance stage.

It should be explicitly noted that the structural model in this study was specified as a full mediation model meaning it excluded direct paths from PEOU and PU to BI and CI. Consequently, while the test results confirm the existence and significance of indirect effects, they do not allow for the classification of mediation types (complementary, competitive, or indirect-only) according to the framework of Zhao et al. (2010), as that classification requires the simultaneous estimation of both direct and indirect paths. This specification limitation is noted and discussed further in the research limitations section.

Testing the Moderating Effect

The seventh hypothesis (H7) examines the role of Digital Literacy as a moderating variable on the $PU \rightarrow ATU$ path. The interaction term was constructed using the two-stage approach (Henseler & Chin, 2010), which is considered most suitable for models with reflective constructs and offers higher statistical power compared to the product-indicator approach.

Table 9. Results of Moderation Effect Testing

	Track	Coefficient (O)	Std. Deviation	t-statistic	p-value	f ²	Decision
H7	$LD \times PU \rightarrow ATU$	0,198	0,072	2,738	0,006	0,180	Accepted

Table 10. Simple slope analysis

Perceived Usefulness -> Attitude Toward Using	
Digital Literacy at +1 SD	0.499
Digital Literacy at -1 SD	0.103
Digital Literacy at the Mean	0.301

The interaction coefficient was positive and significant ($\beta = 0.198$; $p = 0.006$), indicating that Digital Literacy strengthens the influence of perceived usefulness on the attitude toward using QRIS. The interaction effect size of $f^2 = 0.180$ is considered large when evaluated against established standards for moderation effects. Aguinis et al. (2005) documented that moderation effects in field research typically exhibit very small effect sizes; thus, the magnitude observed in this study represents a substantively strong contingency effect, rather than one that is merely statistically significant. To determine the specific form of moderation, a simple slope analysis was conducted at three levels of Digital Literacy.

Table 11. Simple Slope Analysis Results: Effect of PU on ATU at Various Levels of Digital Literacy

Digital Literacy Level	PU $\rightarrow$ ATU Coefficient	Std. Deviation	t-statistic	p-value	Information
High (+1 SD)	0,499	0,116	4,320	0,000	Significant
Average (Mean)	0,301	0,094	3,207	0,001	Significant
Low (-1 SD)	0,103	0,121	0,852	0,394	Not Significant

The analysis results show a clear gradient. For respondents with high digital literacy, the effect of perceived usefulness on attitudes reached 0.499 and was highly significant. At the average literacy level, this effect decreased to 0.301. For respondents with low digital literacy, the coefficient decreased to 0.103 with a $p = 0.394$ and a confidence interval containing zero $[-0.131; 0.338]$, making it statistically insignificant. Thus, the identified moderation is not

merely a gradual strengthening effect, but rather determines whether the relationship itself holds. In the low digital literacy group, perceived usefulness loses all its explanatory power on attitude formation. The theoretical implications of these findings are outlined in the discussion section.

Coefficient of Determination and Effect Size

The model's ability to explain the variance of the endogenous construct is assessed using the R^2 value, while the relative contribution of each predictor is assessed using the effect size f^2 (Cohen, 1988).

Table 12. Coefficient of Determination (R^2)

Endogenous Construct	R^2	R^2 Adjusted	Category
<i>Attitude Toward Using</i> (ATU)	0,556	0,544	Moderate
<i>Perceived Usefulness</i> (PU)	0,371	0,366	Weak–Moderate
<i>Continuance Intention</i> (CI)	0,309	0,304	Weak–Moderate
<i>Behavioral Intention</i> (BI)	0,299	0,294	Weak–Moderate

The "Attitude Toward Using" (ATU) construct exhibits the highest explanatory power, with 55.6% of its variance explained by the combination of PEOU, PU, LD, and the $LD \times PU$ interaction term. The only slightly lower adjusted R^2 value (0.544) indicates that adding predictors to this construct does not incur a significant complexity penalty.

Table 13. Effect Size (f^2)

Track	f^2	Category
PEOU $\rightarrow$ PU	0,589	Large
BI $\rightarrow$ CI	0,447	Large
ATU $\rightarrow$ BI	0,426	Large
PEOU $\rightarrow$ ATU	0,320	Medium
$LD \times PU \rightarrow$ ATU	0,180	Medium (large for interaction effect)
PU $\rightarrow$ ATU	0,104	Small–Medium
LD $\rightarrow$ ATU	0,076	Small

The R^2 values for the BI (0.299) and CI (0.309) constructs are comparatively lower. It should be noted that these magnitudes are a direct consequence of the full mediation model specification: the BI construct accepts only a single predictor (ATU), as does the CI construct (which accepts only BI). With only one predictor for each construct, the model's explanatory capacity is structurally limited. This does not indicate weak relationships between constructs, as evidenced by the substantial f^2 values for both paths (0.426 and 0.447), but rather reflects a specification choice that intentionally adheres to the original TAM postulates regarding the perception–attitude–intention–continuance chain.

Model Predictive Relevance

Predictive relevance was assessed using the PLS predict procedure with ten-fold cross-validation and ten repetitions, following the guidelines of Shmueli et al. (2019).

Table 14. PLSpredict results at the latent construct level

Construct	Q^2 predict	RMSE	MAE
Attitude Toward Using	0,454	0,760	0,537
Perceived Usefulness	0,354	0,827	0,561
Behavioral Intention	0,353	0,821	0,611
Continuance Intention	0,205	0,914	0,642

All endogenous constructs exhibit Q^2 predict values greater than zero, indicating that the model possesses predictive relevance regarding data outside the estimation sample. The highest Q^2 predict value is observed for the ATU construct (0.454), consistent with it also having the highest R^2 value.

The next step involves comparing the PLS model's prediction errors with those of a linear regression model (linear model benchmark). An examination of the prediction error distributions reveals that all indicators exhibit significantly skewed distributions according to the Cramér-von Mises test ($p < 0.001$), with the highest degree of skewness found in the Continuance Intention indicator (skewness values ranging from -0.742 to -1.067). Shmueli et al. (2019) explicitly state that when error distributions are highly asymmetric, Mean Absolute Error (MAE) is a more appropriate comparative metric than Root Mean Squared Error (RMSE), as RMSE places excessive weight on extreme errors resulting from a small number of outlying observations. Based on this consideration, the comparison in this study utilizes MAE.

Table 15. Comparison of MAE between the PLS-SEM Model and the Linear Model (LM)

Indicator	MAE PLS-SEM	MAE LM	Difference	Information
CI1	0,483	0,529	-0,046	PLS is superior
CI2	0,561	0,599	-0,038	PLS is superior
CI3	0,564	0,596	-0,032	PLS is superior
CI4	0,605	0,634	-0,029	PLS is superior

All indicators for the Continuance Intention construct exhibited lower MAE values in the PLS model compared to the linear regression model. Based on the criteria established by Shmueli et al. (2019), the fact that all indicators for the target construct yielded smaller errors than the benchmark indicates that the model possesses high predictive power regarding the intention to continue using QRIS. As a supplementary analysis, a Cross-Validated Predictive Ability Test (CVPAT) developed by Liengaard et al. (2021) was conducted. When compared against the indicator average benchmark, the model demonstrated significant superiority across all endogenous constructs as well as overall (mean error difference = -0.194 ; $p < 0.001$), confirming that the model possesses predictive capability that substantially surpasses naive, mean-based predictions.

Summary of Hypothesis Testing Results

Table 16. Summary of Hypothesis Testing Results

Hypothesis	Statements	Coefficient	p-value	Decision
H1	PEOU has a positive effect on PU	0,609	0,000	Accepted
H2	PEOU has a positive effect on ATU	0,482	0,000	Accepted
H3	PU has a positive effect on ATU	0,301	0,001	Accepted
H4	ATU has a positive effect on BI	0,547	0,000	Accepted
H5	BI has a positive effect on CI	0,556	0,000	Accepted
H6	ATU and BI mediate the effect of PEOU and PU on CI	0,056–0,304	0,000–0,031	Accepted
H7	LD moderates the effect of PU on ATU	0,198	0,006	Accepted

Perceived ease of use makes the largest contribution to attitude formation ($\beta = 0.482$) as well as to perceived usefulness ($\beta = 0.609$). These figures establish operational ease as the primary foundation for QRIS acceptance within the studied population. This pattern can be explained by the characteristics of the technology under study. QRIS offers a different method for performing a routine activity payment meaning the promised benefits are incremental and relatively easy for users to anticipate. Conversely, the operational experience is direct and immediately felt. In this configuration, ease of use serves as a prerequisite for forming a

positive assessment and acts as the pathway through which perceived usefulness itself is constructed. This finding aligns with Venkatesh's (2000) proposition that user assessments during the initial experience stage are shaped by anchoring to beliefs regarding one's own ability to operate the technology.

The $ATU \rightarrow BI \rightarrow CI$ pathway proved significant, with comparable strength across both segments, providing empirical support for extending TAM into the post-adoption stage as conceptualized by Bhattacharjee (2001). The significance of the five-stage mediation chain $PEOU \rightarrow PU \rightarrow ATU \rightarrow BI \rightarrow CI$ ($\beta = 0.056$; $p = 0.031$) reinforces this conclusion. Long causal chains are subject to multiplicative attenuation, meaning small-scale effects are often difficult to detect. The persistence of statistical significance indicates that the hypothesized mechanism remains intact across the entire chain: the initial perception of ease leaves a measurable imprint that extends to the intention to continue using QRIS. It should be emphasized that the construct being measured is the intention to continue, not the actual continuation of the behavior.

The most substantive finding of this study lies in the simple slope analysis. Among respondents with high digital literacy, the influence of perceived usefulness on attitude was recorded at 0.499, significant at the 1% level. Conversely, among respondents with low digital literacy, the coefficient dropped to 0.103 ($p = 0.394$), with a confidence interval that included zero. This difference is qualitative in nature. In the low-literacy group, no relationship was detected between perceived usefulness and attitude. These findings indicate that the conversion of recognized utility into a positive attitude is not a uniform process across all users; rather, it is a process contingent upon specific capabilities.

A theoretical explanation can be formulated using Bandura's (1977) distinction between outcome expectancy and efficacy expectancy. Perceived usefulness is essentially a form of outcome expectancy the belief that using technology will yield desired consequences. Bandura asserts that outcome expectancy does not generate a behavioral tendency unless accompanied by the belief that the individual is capable of performing the necessary behavior. Within this framework, digital literacy represents the capability that determines whether outcome expectancy can be internalized as personally relevant. Consequently, for low-literacy users, the recognition of QRIS's utility remains an abstract proposition about the technology rather than an anticipation of a personal experience. Respondents may agree that QRIS accelerates transactions without linking that statement to their own self-assessment as users, simply because they cannot yet envision themselves reliably realizing that benefit. In the tradition of Fishbein and Ajzen (1975), an attitude constitutes a self-referential evaluation of an object; thus, utility that has not been personally appropriated fails to convert into an attitude. Therefore, digital literacy functions as a boundary condition determining the applicability of the TAM mechanism, rather than as a competing predictor that shifts the level of attitude. These findings extend the discussion on the second-level digital divide (Van Deursen & Van Dijk, 2019): the shift in inequality from access to skills manifests not merely as differences in adoption rates across groups, but as differences in the adoption mechanisms themselves.

Digital literacy also demonstrates a significant direct influence on attitude ($\beta = 0.247$; $p = 0.016$), albeit with a small effect size. This path was included as a methodological prerequisite for the moderation test and is treated as an ancillary finding. A comparison of the two mechanisms yields meaningful insights. The indirect effect via the main effect path ($DL \rightarrow ATU \rightarrow BI \rightarrow CI$) is 0.075 ($p = 0.063$), whereas the effect via the moderation path ($DL \times PU \rightarrow ATU \rightarrow BI \rightarrow CI$) is 0.060 ($p = 0.019$). Consequently, digital literacy contributes to continuance intention more effectively through its role in conditioning the conversion of

usefulness than through its direct contribution to attitude. This pattern reinforces the conceptualization of digital literacy as a boundary condition.

Conclusion

This study confirms that the continued use of QRIS among GMIM youth is shaped through a coherent sequence of technological perceptions, attitudes, and behavioral intentions. Perceived ease of use emerged as the strongest initial driver, directly improving attitudes toward QRIS and strengthening perceptions of its usefulness. Positive attitudes subsequently increased behavioral intention, which became a substantial predictor of continuance intention. The significant serial mediation pathway from perceived ease of use through perceived usefulness, attitude, and behavioral intention to continuance intention demonstrates that sustained QRIS adoption should be understood as a gradual psychological process rather than merely the result of recognizing its practical benefits. Digital literacy plays a particularly important role in this process. Although it directly contributes to a more positive attitude toward QRIS, its principal contribution lies in strengthening the conversion of perceived usefulness into attitude. The usefulness of QRIS significantly influences attitudes among users with high digital literacy, whereas this relationship is not significant among users with low digital literacy. Accordingly, initiatives intended to sustain QRIS usage should combine simple and reliable system design with practical digital-literacy training, particularly in application operation, transaction security, feature comprehension, and technical problem-solving. Nevertheless, because this study used a cross-sectional design, purposive sampling, and self-reported intentions within a specific religious youth community, its findings should not be interpreted as evidence of actual continued behavior or generalized without caution. Future research should employ longitudinal designs, measure actual usage, use more diverse samples, and examine additional post-adoption factors such as satisfaction, trust, habit, and perceived risk.

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