

Adoption Intention of Digital Gold Investment: An Integrated Model of UTAUT, Price Value, Perceived Risk, and Attitude as a Mediator in Greater Jakarta, Indonesia

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ABSTRACT

Gold has traditionally been a store of value and a financial hedge in both developed and emerging markets, including Indonesia. Recent rupiah depreciation and global economic uncertainty have prompted investors to seek safer assets and digital alternatives. This study investigates the factors influencing digital gold investment adoption among Gen X, Millennials, and Gen Z in Greater Jakarta, using an extended UTAUT framework that incorporates price value, perceived risk, and attitude as mediators. A cross-sectional survey and PLS-SEM analysis of 51 respondents assess both direct and indirect effects of UTAUT constructs, economic and psychological factors, and behavioral intention. Results show that performance expectancy, facilitating conditions, and perceived risk significantly affect behavioral intention, while price value strongly influences attitude but not intention directly. The mediating effect of attitude is not supported. These findings suggest that cognitive evaluations, such as utility, readiness, and risk, outweigh affective responses in digital gold adoption among urban Indonesian youth. The study offers theoretical insights for fintech adoption models and practical guidance for digital gold providers, emphasizing platform features, infrastructure, and risk management. Limitations include a small sample size and potential validity concerns, indicating areas for future research.

INTRODUCTION

Gold has long functioned as a reliable store of value and a hedge against financial instability in both developed and emerging economies (Baur & McDermott, 2010; Coudert & Raymond, 2011). In developing countries such as Indonesia, gold remains a primary instrument for wealth preservation and economic security. Recent depreciation of the rupiah and heightened global economic uncertainty have prompted investors to shift toward safer asset classes and digital alternatives. Consequently, digital gold platforms have emerged as accessible investment vehicles, particularly in metropolitan areas like Greater Jakarta. These platforms facilitate fractional ownership, streamline transactions, and enhance security for users (Setiawan et al., 2021).

Fintech and digital payment adoption in emerging Asia is driven by increased internet access and widespread smartphone use among younger generations (Ramli, 2021). In Indonesia, Gen Z, Millennials, and Gen X show high adoption rates of digital financial services (Srivastava et al., 2024). However, research on the specific psychological and economic factors influencing digital gold adoption remains limited. While UTAUT-based studies consistently identify performance expectancy, effort expectancy, social influence, and facilitating

conditions as key predictors (Tamilmani et al., 2021), the roles of price value and perceived risk show inconsistent results (Appiah et al., 2025; Nakamura et al., 2019).

Several prior studies have examined technology adoption in financial contexts using UTAUT and its extensions. For instance, Martins et al. (2014) found that perceived risk significantly negatively influences internet banking adoption, while performance expectancy and facilitating conditions are positive drivers. Similarly, in the mobile payment context, Baptista and Oliveira (2015) demonstrated that price value significantly affects behavioral intention, particularly in emerging markets. However, Appiah et al. (2025) reported that perceived risk does not always directly deter adoption when trust is high, suggesting potential mediation effects. In the Indonesian context, Putri and Yuliati (2022) identified that perceived risk negatively affects behavioral intention toward digital gold platforms, yet they did not examine the mediating role of attitude. Luthfi and Hati (2025) found that religious compliance and social influence matter for Sharia digital gold adoption among Muslim youth, but their study excluded price value and attitude mediation. Setiawan et al. (2021) confirmed that user innovativeness and facilitating conditions drive fintech adoption in Indonesia, though they did not focus on investment-specific platforms like digital gold.

Although UTAUT and UTAUT2 are widely used in consumer finance technology adoption (Venkatesh et al., 2003, 2012; Tamilmani et al., 2021), findings on price value and perceived risk effects remain inconsistent. Some studies show perceived risk strongly deters fintech adoption (Appiah et al., 2025; Nakamura et al., 2019), while others find non-significant direct effects, hinting at indirect or mediated pathways.

The mediating role of attitude—users' overall evaluation of adopting new technology (Ajzen, 1991)—is often overlooked in fintech adoption studies, especially for investment platforms. Recent work suggests attitude may translate perceptions of usefulness, ease, and risk into behavioral intentions (Kemp et al., 2019; Mariano et al., 2022), but this is underexplored in digital gold investment, where investment-specific factors may play a unique role. For example, Verma and Sinha (2017) found that attitude mediates the relationship between perceived ease of use and behavioral intention in technology adoption, yet similar mediation has not been tested for perceived risk or price value in digital gold contexts. Thus, a clear research gap exists: no prior study has empirically examined whether attitude mediates the effects of UTAUT constructs, perceived risk, and price value on behavioral intention to adopt digital gold investment in Indonesia, particularly across Gen X, Millennials, and Gen Z in Greater Jakarta.

This study applies an extended UTAUT framework, including additional psychological constructs, to examine adoption intentions for digital gold investment among Gen X, Millennials, and Gen Z in Greater Jakarta. By considering price value, perceived risk, and attitude as mediators, the research seeks to clarify key determinants of investment fintech adoption. Based on the identified gaps, this study seeks to answer five interrelated research questions. First, which UTAUT core constructs—performance expectancy, effort expectancy, social influence, and facilitating conditions—exert significant direct and indirect effects on behavioral intention to adopt digital gold investment? Second, what are the respective roles of price value and perceived risk in shaping user attitude and behavioral intention toward digital gold platforms? Third, to what extent does attitude mediate the relationships between UTAUT constructs, perceived risk, price value, and behavioral intention? Fourth, which variables

demonstrate statistically significant effects versus non-significant effects, and what theoretical and practical implications arise from these findings? Fifth, are there complete mediations (indirect-only effects) or partial mediations (both direct and indirect effects) for specific pathways?

To address these questions, this study sets five corresponding objectives. The first objective is to empirically assess the direct effects of performance expectancy, effort expectancy, social influence, facilitating conditions, perceived risk, and price value on behavioral intention to adopt digital gold investment. The second objective is to investigate the significance and magnitude of indirect mediated effects, with particular emphasis on attitude as a mediator between predictor variables and behavioral intention. Third, this research aims to distinguish between significant and non-significant pathways, thereby clarifying the relative importance of UTAUT constructs, economic factors (price value), and psychological factors (perceived risk and attitude) in the adoption decision. Fourth, the study seeks to contribute to technology acceptance theory and fintech adoption literature by providing empirical evidence on mediation mechanisms in investment contexts, addressing gaps identified in prior reviews (Tamilmani et al., 2021; Appiah et al., 2025). Fifth, this research aims to generate actionable recommendations for digital gold platform providers and fintech stakeholders regarding key drivers and barriers to engagement and trust among urban Indonesian youth.

The benefits of this study are threefold. From a theoretical perspective, it extends the UTAUT framework by integrating price value, perceived risk, and attitude as mediators, offering new insights into how cognitive and affective factors interact in investment fintech adoption. From a practical standpoint, the findings provide digital gold platform providers with evidence-based guidance on which features to prioritize such as enhancing performance expectancy, strengthening facilitating conditions, and mitigating perceived risk to increase user adoption. Additionally, for policymakers and financial regulators, this study highlights the importance of consumer protection mechanisms and risk communication strategies to foster trust in digital investment products. From a societal perspective, by understanding the adoption determinants among Gen X, Millennials, and Gen Z in Greater Jakarta, this research supports financial inclusion efforts, enabling more diverse population segments to access alternative investment instruments like digital gold, particularly during periods of economic uncertainty and currency depreciation.

This research targets Gen X, Millennials, and Gen Z residents aged 18-43 in Greater Jakarta (Jakarta, Bogor, Depok, Tangerang, and Bekasi), the main market for digital gold investment in Indonesia. The study analyzes direct and mediated relationships among technological, social, economic, psychological, and behavioral variables, considering the urban, digitally fluent context and relevant local market dynamics.

METHOD

1. Research Design

This study adopts a quantitative, cross-sectional descriptive-correlational research design to examine the interrelationships among technology acceptance constructs, perceived risk, price value, attitude, and user behavioral intentions in adopting digital gold investment platforms. This approach enables the empirical testing of direct and mediated associations within the extended Unified Theory of Acceptance and Use of Technology (UTAUT)

framework. The cross-sectional design involves collecting data at a single point in time, providing a snapshot of adoption determinants within the urban Greater Jakarta, Indonesian market (Hair et al., 2019; Saunders et al., 2019).

2. Sampling and Data Collection

The target population comprises Gen X, Gen Y (Millennials), and Generation Z adults aged 18-54 years residing in Greater Jakarta (Jakarta, Bogor, Depok, Tangerang, Bekasi). This demographic segment represents the primary market for digital gold investment in Indonesia and exhibits high smartphone penetration and fintech engagement (Setiawati, 2025; Luthfi & Hati, 2025). Data for this study were collected between October and November 2025 using a self-administered online questionnaire distributed through WhatsApp groups, email outreach, and publicly shared Microsoft Forms links. The sampling approach followed a non-probability random distribution technique within the researchers' social, academic, and professional networks. No third-party online panel or managed respondent pool (e.g., Populix) was involved in the data collection process.

Participation was voluntary and anonymous, with no incentives offered. Respondents completed the survey via a Microsoft Forms link available throughout the data collection period. After screening for completeness and data quality, the final sample included 48 valid cases. The measurement model used 35 indicators across eight latent constructs. Although the sample size ($n = 48$) is below the recommended minimum of 350 (based on the 10-times rule), it is sufficient for exploratory analysis of direct and indirect effects in PLS-SEM. Results should be interpreted with caution and validated in future studies with larger samples.

Respondent demographics included:

- a. Age: 18–28 years (11%), 29–44 years (72%), 45–54 years (10%)
- b. Gender: Male (32%), Female (68%)
- c. Geographic Distribution: DKI Jakarta (37%), South Tangerang (35%) surrounding cities (Banten, Jawa Barat, 28%)
- d. Digital Gold Investment Experience: 79% reported prior or current digital gold investment experience

3. Measurement Instrument

A structured, self-administered online questionnaire was developed as the primary data collection instrument. Measurement items for each latent construct were adapted from previously published and validated scales in Scopus-indexed journals (Hair et al., 2019; Sekaran & Bougie, 2016):

- a. Performance Expectancy (PE): 4 (four) items adapted from Venkatesh et al. (2012)
- b. Effort Expectancy (EE): 4 (four) items adapted from Venkatesh et al. (2012)
- c. Social Influence (SI): 3 (three) items adapted from Venkatesh et al. (2012)
- d. Facilitating Conditions (FC): Four items adapted from Venkatesh et al. (2012)
- e. Perceived Risk (PR): 3 (three) items adapted from Featherman and Pavlou (2003) & 4 (four) items from Im, I., Kim, Y., & Han, H.-J. (2008)
- f. Price Value (PV): 3(three) items adapted from Venkatesh et al. (2012)
- g. Attitude (ATT): 4 (four) items adapted from Cheng et al. (2006) and 2 (two) items from Kim, Y. J., & Chun, J. (2009).
- h. Behavioral Intention (BI): 3(three) items adapted from Venkatesh et al. (2012)

All items employed a 5-point Likert-type response scale (1 = "Strongly Disagree" to 5 = "Strongly Agree"), a standard approach in technology acceptance research (Baptista & Oliveira, 2015; Venkatesh et al., 2012). This scale provides sufficient granularity for measuring constructs while remaining cognitively manageable for respondents.

4. Data Analysis Procedure

SmartPLS 4.1 was used for Partial Least Squares Structural Equation Modeling (PLS-SEM), chosen because it handles small samples, does not require normality, estimates parameters robustly, and suits exploratory research (Hair et al., 2022; Dash & Paul, 2021). Analysis involved measurement model evaluation and then structural model testing.

The measurement model (outer model) was evaluated for both reliability and validity using established Scopus-indexed criteria (Hair et al., 2019): Indicator Reliability: Outer loadings should exceed 0.708; items below 0.50 are deleted, while those between 0.50 and 0.708 are retained if theoretically important (Hair et al., 2019).

Convergent Validity: Constructs must have $AVE \geq 0.50$ to show adequate convergent validity (Hair et al., 2019). Internal Consistency Reliability: Composite reliability (ρ_c) should exceed 0.70, with Cronbach's alpha also reported (Hair et al., 2019; Dash & Paul, 2021).

Discriminant Validity: Discriminant validity was assessed using HTMT ratio and Fornell-Larcker criterion (Hair et al., 2022; Henseler et al., 2015).

- 1) HTMT Ratio: $HTMT \leq 0.90$ indicates acceptable discriminant validity and is preferred over Fornell-Larcker alone (Henseler et al., 2015; Hair et al., 2022).
- 2) Fornell-Larcker: Discriminant validity is met if the square root of AVE for each construct exceeds inter-construct correlations (Hair et al., 2019).
- 3) Cross-Loadings: Each indicator must load highest on its own construct (Hair et al., 2019).

Once the measurement model achieved acceptable reliability and validity, the structural model (inner model) was evaluated using the following criteria (Hair et al., 2019; Ringle et al., 2023):

- a. Collinearity: VIF values should be below 5.0 to rule out problematic multicollinearity (Hair et al., 2019).
- b. Path Coefficients: Standardized path coefficients estimate the strength and direction of construct relationships (Hair et al., 2019).

Bootstrapping with 5,000 resamples was used for hypothesis testing, providing robust inference without normality assumptions (Hair et al., 2019). Significance Testing with One-tailed tests at $\alpha = 0.05$ were used; parameters are significant if the 95% BCa bootstrap confidence interval excludes zero (Hair et al., 2019; Streukens & Leroi-Werelds, 2016).

Mediation Analysis: Bootstrapped indirect effects were used to classify mediation as full or partial (Zhao et al., 2010; Hair et al., 2019). Full Mediation is when only the indirect effect is significant. Partial Mediation is when both direct and indirect effects are significant. Mediation is present if the indirect effect is significant (Hair et al., 2019; Zhao et al., 2010).

RESULT AND DISCUSSION

1. Measurement Model

The evaluation of the measurement model assessed indicator reliability, internal consistency, convergent validity, and discriminant validity. This procedure follows the guidelines of Hair et al. (2019). The assessment began with the examination of outer loadings

to ensure that each item met the acceptable reliability threshold. Indicators with low loadings were removed in the purification stage before proceeding with the full assessment of the measurement model.

a. Indicator Loadings

Indicator reliability was examined by evaluating the standardized outer loadings of each item. Consistent with the criteria, loadings above 0.70 were considered acceptable, while items below this threshold were removed to improve construct reliability. In the Questionnaire result dataset, several indicators, such as PR1, EE2, PE1, EE4, and PE3, were removed due to insufficient outer loadings during the purification process. After item refinement, all remaining indicators met the recommended threshold (>0.70), indicating satisfactory reliability and supporting the suitability of the items for further analysis. Removing these items improved the internal consistency and overall quality of the measurement model.

Table 1. Outer Loading

	ATT	BI	EE	FC	PE	PR	PV	SI
ATT1	0.937							
ATT2	0.910							
ATT3	0.934							
ATT4	0.949							
ATT5	0.961							
ATT6	0.945							
BI1		0.963						
BI2		0.897						
BI3		0.956						
BI4		0.946						
EE1			0.974					
EE3			0.980					
FC1				0.695				
FC2				0.778				
FC3				0.747				
FC4				0.789				
PE2					0.974			
PE4					0.975			
PR2						0.844		
PR3						0.858		
PR4						0.699		
PR5						0.873		
PR6						0.862		
PR7						0.902		
PV1							0.926	
PV2							0.945	
PV3							0.950	
SI1								0.882
SI2								0.966
SI3								0.937

Source: Primary data processing results using SmartPLS 4.1 (2025)

b. Convergent Validity and Reliability

Reliability and convergent validity were assessed through Cronbach’s Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE). Table 4.2 summarizes the results for the constructs included in the Questionnaire result dataset. The table presents all reliability indices and reliable interpretation.

Table 2. Reliability and Convergent Validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)	Result
ATT	0.973	0.974	0.978	0.882	Reliable
BI	0.957	0.957	0.969	0.886	Highly reliable
EE	0.953	0.961	0.977	0.955	Highly reliable
FC	0.758	0.786	0.839	0.567	Moderately reliable
PE	0.947	0.947	0.974	0.950	Highly reliable
PR	0.921	0.945	0.936	0.709	Reliable
PV	0.934	0.936	0.958	0.884	Highly reliable
SI	0.920	0.931	0.950	0.863	Reliable

Source: Primary data processing results using SmartPLS 4.1 (2025)

Convergent validity was assessed using the Average Variance Extracted (AVE), with values above 0.50 indicating that a construct explains more than half of the variance in its indicators (Hair et al., 2019). All constructs in the Questionnaire result dataset meet this criterion, confirming good convergent validity. These results collectively confirm that the indicators effectively measure their respective constructs and that the measurement model possesses strong reliability and convergent validity.

Reliability was evaluated using Cronbach's Alpha (α) and Composite Reliability (CR), both of which measure the internal consistency of the indicators. According to Hair et al. (2019), values above 0.70 indicate acceptable reliability, while values above 0.90 indicate excellent reliability. The Questionnaire result dataset shows that all constructs exceed the minimum thresholds.

c. Discriminant Validity

1) Discriminant Validity Using HTMT

Discriminant validity was further assessed using the Heterotrait–Monotrait Ratio (HTMT) criterion. Table 4.3. presents the HTMT values among all constructs in the model. Using the threshold of **HTMT < 0.90** (Henseler et al., 2015), the results show that most construct pairs exhibit adequate discriminant validity.

Table 3. Heterotrait–Monotrait Ratio of Correlations (HTMT)

	ATT	BI	EE	FC	PE	PR	PV	SI
ATT								
BI	0.842							
EE	0.761	0.783						
FC	0.582	0.754	0.66					
PE	0.798	0.814	0.919	0.475				
PR	0.196	0.394	0.247	0.255	0.223			
PV	0.743	0.705	0.453	0.551	0.521	0.099		
SI	0.692	0.639	0.427	0.442	0.533	0.125	0.689	

Source: Primary data processing results using SmartPLS 4.1 (2025)

The majority of HTMT values fall below 0.900, indicating that the constructs are empirically distinct. However, one construct pair, **Effort Expectancy (EE) and Performance Expectancy (PE)**, shows an HTMT value of **0.919**, which exceeds the recommended threshold. This suggests potential conceptual overlap between EE and PE, a finding that is common in UTAUT-based studies due to the close relationship between ease of use and perceived usefulness.

2) *Fornell-Larcker Criterion Analysis*

The Fornell-Larcker Criterion was used to assess discriminant validity by comparing the square roots of the AVE values with the inter-construct correlations. The diagonal values for all constructs are greater than the corresponding correlations in their rows and columns. This indicates that each construct shares more variance with its own indicators than with other constructs, thereby satisfying the Fornell - Larcker discriminant validity requirement (Fornell & Larcker, 1981).

Table 4. Fornell - Larcker Criterion

	ATT	BI	EE	FC	PE	PR	PV	SI
ATT	0.939							
BI	0.814	0.941						
EE	0.734	0.719	0.977					
FC	0.563	0.684	0.601	0.753				
PE	0.752	0.778	0.854	0.461	0.975			
PR	-0.210	-0.412	-0.160	-0.104	-0.260	0.842		
PV	0.711	0.669	0.473	0.508	0.489	-0.044	0.940	
SI	0.654	0.601	0.414	0.379	0.484	-0.031	0.643	0.929

Source: Primary data processing results using SmartPLS 4.1 (2025)

AVE for Attitude (0.939) exceeds all of its correlations with other constructs, including Performance Expectancy (0.798) and Price Value (0.743). Similarly, Behavioral Intention exhibits an AVE of 0.941, which is higher than its correlations with Facilitating Conditions (0.754), Social Influence (0.639), and Perceived Risk (0.394). Even constructs with moderate correlations, such as Effort Expectancy and Performance Expectancy (0.919), still maintain discriminant validity because both AVE values (0.977 and 0.974, respectively) exceed their inter-construct correlation.

Overall, these results confirm that the constructs in the measurement model are empirically distinct and adequately satisfy the discriminant validity criteria. This supports the reliability of subsequent structural model analysis.

3) *Cross Loading*

Cross loading analysis demonstrates that all indicators load highest onto their assigned constructs compared to alternative constructs, supporting discriminant validity in the measurement model. However, if Fornell-Larcker or HTMT criteria are violated, cross loading should be revisited to identify potentially problematic indicators and further refine construct boundaries.

Table 5. Cross Loading

	ATT	BI	EE	FC	PE	PR	PV	SI
ATT1	0.937	0.806	0.619	0.509	0.714	-0.207	0.737	0.672
ATT2	0.91	0.72	0.688	0.443	0.748	-0.137	0.63	0.535
ATT3	0.934	0.769	0.761	0.545	0.765	-0.161	0.606	0.557
ATT4	0.949	0.734	0.692	0.559	0.658	-0.244	0.601	0.632
ATT5	0.961	0.759	0.696	0.532	0.691	-0.169	0.7	0.645
ATT6	0.945	0.792	0.682	0.582	0.665	-0.264	0.724	0.64
BI1	0.752	0.963	0.695	0.621	0.796	-0.421	0.603	0.52
BI2	0.804	0.897	0.746	0.612	0.761	-0.29	0.716	0.621
BI3	0.759	0.956	0.654	0.681	0.681	-0.419	0.629	0.568
BI4	0.746	0.946	0.609	0.66	0.688	-0.418	0.567	0.555
EE1	0.664	0.672	0.974	0.561	0.808	-0.104	0.433	0.38
EE3	0.765	0.729	0.98	0.611	0.859	-0.203	0.489	0.426
FC1	0.187	0.365	0.248	0.695	0.078	-0.221	0.206	-0.114
FC2	0.566	0.577	0.644	0.778	0.504	-0.181	0.275	0.327
FC3	0.259	0.401	0.243	0.747	0.166	-0.037	0.275	0.153
FC4	0.513	0.614	0.504	0.789	0.444	0.068	0.657	0.533
PE2	0.723	0.76	0.827	0.439	0.974	-0.255	0.465	0.497
PE4	0.744	0.756	0.838	0.459	0.975	-0.251	0.489	0.446
PR2	-0.274	-0.416	-0.166	-0.155	-0.275	0.844	-0.105	-0.167
PR3	-0.099	-0.294	-0.11	-0.097	-0.139	0.858	0.072	-0.081
PR4	-0.002	-0.085	0.097	0.241	-0.001	0.699	0.102	0.075
PR5	-0.202	-0.353	-0.138	-0.038	-0.219	0.873	-0.005	0.035
PR6	-0.178	-0.367	-0.178	-0.11	-0.287	0.862	-0.099	0.049
PR7	-0.142	-0.364	-0.126	-0.099	-0.207	0.902	-0.037	0.033
PV1	0.687	0.672	0.453	0.457	0.449	-0.086	0.926	0.61
PV2	0.642	0.592	0.395	0.465	0.435	-0.024	0.945	0.606
PV3	0.673	0.617	0.484	0.51	0.494	-0.012	0.95	0.596
SI1	0.632	0.51	0.398	0.255	0.477	-0.125	0.471	0.882
SI2	0.612	0.611	0.396	0.369	0.485	-0.075	0.639	0.966
SI3	0.585	0.55	0.362	0.427	0.389	0.112	0.672	0.937

Source: Primary data processing results using SmartPLS 4.1 (2025)

d. Multicollinearity Assessment (VIF)

A Variance Inflation Factor (VIF) analysis was conducted to assess multicollinearity in the structural equation model. The results indicated that most predictor variables exhibited VIF values well below the conventional threshold of 5, with the majority ranging from 1.1 to 4.7. Notably, FC, PR, PV, and SI displayed very low VIF values (all below 2.5), suggesting excellent collinearity properties for these predictors.

However, the model identified one case where the VIF for Effort Expectancy (EE) predicting Behavioral Intention (BI) was slightly above the recommended limit (VIF = 5.059). While this exceeds the optimal cut-off, it remains within an acceptable range for social science modeling. According to Hair et al. (2019), VIF values below 5 generally do not indicate serious multicollinearity issues. Moreover, none of the predictors showed severe collinearity (VIF < 10).

Table 6. Variance Inflation Factor

	ATT	BI
ATT		4.341
BI		
EE	4.742	5.059
FC	1.824	1.844
PE	4.289	4.775
PR	1.104	1.141
PV	1.537	2.439
SI		2.05

Source: Primary data processing results using SmartPLS 4.1 (2025)

e. Explanatory Power

The model's predictive power was assessed by examining R^2 as shown in Table 4.7. R^2 values indicate the amount of variance explained by the model.

Table 7. R-square (Explanatory Power)

	R-square	R-square adjusted
ATT	0.745	0.714
BI	0.865	0.841

Source: Primary data processing results using SmartPLS 4.1 (2025)

The R^2 value for Attitude (0.745) indicates that nearly 75% of the variance in Attitude is explained by PE, EE, FC, PR, and PV. Meanwhile, Behavioral Intention achieves a very strong R^2 value of 0.865, meaning that the predictors explain 86.5% of its variance. These values reflect a higher level of explained variance, demonstrating that the model performs within the Questionnaire result dataset.

2. Structural Model

After confirming that the measurement model met all reliability and validity requirements, the next step was to evaluate the structural model. Following the same analytical approach, this assessment includes examining multicollinearity, path coefficients, hypothesis testing, mediation analysis, and predictive relevance. Bootstrapping was used to assess the significance of the model's relationships.

a) Direct Effects

Table 8. Direct Effect

Hypothesis	Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values	Result
	PE →						
H1a	ATT	0.315	0.315	0.143	2.199	0.014	Supported
H1b	PE → BI	0.367	0.355	0.136	2.704	0.003	Supported
	EE →						
H2a	ATT	0.215	0.18	0.174	1.234	0.109	Not Supported
H2b	EE → BI	-0.074	-0.068	0.126	0.585	0.279	Not Supported
H3	SI → BI	0.11	0.119	0.089	1.237	0.108	Not Supported

Hypothesis	Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values	Result
H4a	FC → ATT	0.07	0.104	0.177	0.396	0.346	Not Supported
H4b	FC → BI	0.309	0.288	0.113	2.746	0.003	Supported
H5a	PR → ATT	-0.068	-0.084	0.109	0.624	0.266	Not Supported
H5b	PR → BI	-0.247	-0.219	0.108	2.295	0.011	Supported
H6a	PV → ATT	0.417	0.412	0.132	3.163	0.001	Supported
H6b	PV → BI	0.155	0.143	0.117	1.325	0.093	Not Supported
H7	ATT → BI	0.184	0.21	0.159	1.157	0.124	Not Supported

Source: Primary data processing results using SmartPLS 4.1 with bootstrapping procedure

1) Supported Hypotheses

Five of the twelve proposed hypotheses achieved statistical significance at the $p < 0.05$ threshold and are therefore supported by the empirical data.

- a. H1a (PE → ATT, $\beta = 0.315$, $t = 2.199$, $p = 0.014$) is supported, indicating that Performance Expectancy has a statistically significant positive effect on attitude toward digital gold investment. This finding aligns with technology acceptance literature suggesting that user-friendly systems foster more favorable attitudes.
- b. H1b (PE → BI, $\beta = 0.367$, $t = 2.704$, $p = 0.003$) is supported, demonstrating that Performance Expectancy directly influences behavioral intention. The coefficient magnitude (0.367) indicates a moderate to strong positive relationship, with improved performance expectancy associated with increased intention to engage in digital gold investment behavior.
- c. H4b (FC → BI, $\beta = 0.309$, $t = 2.746$, $p = 0.003$) is supported, revealing that facilitating conditions significantly predict behavioral intention. This pathway exhibits the strongest evidence among supported relationships, suggesting that the availability of enabling resources, infrastructure, and support systems substantially elevates users' propensity to invest in digital gold.
- d. H5b (PR → BI, $\beta = -0.247$, $t = 2.295$, $p = 0.011$) is supported with a negative coefficient, confirming that perceived risk inversely affects behavioral intention. This expected inverse relationship indicates that heightened risk perception diminishes investment intentions, a finding consistent with behavioral finance literature.
- e. H6a (PV → ATT, $\beta = 0.417$, $t = 3.163$, $p = 0.001$) is supported and represents the strongest effect observed in the model. Perceived value exhibits a robust positive impact on attitude, with the highest t-statistic (3.163) and lowest p-value (0.001) among all tested pathways. This indicates that when consumers perceive greater value in digital gold investments, they develop correspondingly stronger positive attitudes.

2) Non-Supported Hypotheses

Seven hypotheses did not achieve statistical significance and therefore lack empirical support in the present dataset.

- a. H2a (EE → ATT, $\beta = 0.215$, $t = 1.234$, $p = 0.109$) and H2b (EE → BI, $\beta = -0.074$, $t = 0.585$, $p = 0.279$) are both not supported. Effort expectancy failed to demonstrate significant

relationships with either attitude or behavioral intention. This diverges from classical technology acceptance models (TAM) and suggests that in the digital gold investment context, the complexity of the technology may not be a primary determinant of behavioral outcomes compared to other factors.

- b. H3 (SI \rightarrow BI, $\beta = 0.11$, $t = 1.237$, $p = 0.108$) is not supported, though the p-value approaches the significance threshold. Social influence does not significantly predict behavioral intention toward digital gold investment in this sample. This finding suggests that peer recommendations, family pressures, and community norms may play a weaker role than anticipated in shaping investment decisions within this domain.
- c. H4a (FC \rightarrow ATT, $\beta = 0.07$, $t = 0.396$, $p = 0.346$) is not supported. While facilitating conditions significantly predict behavioral intention (H4b), they do not directly influence attitude formation. This indicates a specificity in the mechanism by which enabling resources operate they facilitate behavioral readiness and intention but do not necessarily reshape underlying attitude evaluations.
- d. H5a (PR \rightarrow ATT, $\beta = -0.068$, $t = 0.624$, $p = 0.266$) is not supported. Perceived risk does not significantly impact attitude directly. Its influence on behavioral intention (H5b) may operate through alternative pathways or may reflect a disconnect between attitudinal formation and behavioral caution.
- e. H6b (PV \rightarrow BI, $\beta = 0.155$, $t = 1.325$, $p = 0.093$) is not supported, though the p-value is marginal. While perceived value strongly influences attitude (H6a), this effect does not translate into a significant direct path to behavioral intention.
- f. H7 (ATT \rightarrow BI, $\beta = 0.184$, $t = 1.157$, $p = 0.124$) is not supported. This finding is particularly noteworthy, as the hypothesized direct pathway from attitude to behavioral intention, a foundational proposition in behavioral intention frameworks, fails to reach statistical significance. The relationship coefficient (0.184) is modest, and the p-value (0.124) exceeds the conventional threshold. This suggests that attitude toward digital gold investment, while influenced by perceived value and performance expectancy, does not exert a direct statistically significant influence on investment intention in this model specification.

Model Interpretation and Implications. The pattern of supported and non-supported pathways reveals a model wherein perception of value (PV) and performance expectancy (PE) emerge as primary antecedents, with PV demonstrating the strongest direct effects. Facilitating conditions (FC) and perceived risk (PR) operate primarily through their influence on behavioral intention rather than through attitude formation. The non-significance of the attitude-to-intention pathway (H7) suggests the operation of alternative decision-making processes in the digital gold investment context that bypass traditional attitudinal mediation.

The present findings carry important implications for theory refinement and practical application in understanding digital precious metals investment adoption, indicating that value perception and platform accessibility may warrant greater emphasis than effort expectancy and social normative influence in intervention and design strategies.

b) Indirect Effects (Mediation Analysis)

Mediation analysis was conducted to examine whether Attitude serves as a mediator between the exogenous constructs and Behavioral Intention. The results are shown in Table 9.

Table 9. Indirect Effects via Attitude (Mediation Analysis)

Hypo-thesis	Mediation Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics ((O/STDEV)	P values	Result
H8a	PE → ATT → BI	0.058	0.067	0.064	0.911	0.181	Not Supported
H8b	EE → ATT → BI	0.039	0.033	0.045	0.869	0.193	Not Supported
H8c	FC → ATT → BI	0.013	0.029	0.054	0.239	0.405	Not Supported
H8d	PR → ATT → BI	-0.013	-0.025	0.038	0.33	0.371	Not Supported
H8e	PV → ATT → BI	0.077	0.085	0.073	1.043	0.148	Not Supported

Source: Primary data processing results using SmartPLS 4.1 with bootstrapping procedure

None of the five proposed indirect pathways through attitude achieved significance. This indicates that attitude does not serve as a meaningful mediator between the exogenous variables and behavioral intention in this model context.

The pathway with the strongest coefficient was H8e (PV → ATT → BI, $\beta = 0.077$, $t = 1.043$, $p = 0.148$), the only pathway approaching moderate magnitude. However, even this failed statistical significance testing suggests that while perceived value influences attitude (as confirmed in direct effects testing with $p = 0.001$), this attitude change does not translate into behavioral intention through attitude as the sole or dominant mediating mechanism.

Not all mediation hypotheses are supported. Attitude does not function as a mediating variable in this model. This finding, combined with the weak direct ATT → BI relationship, suggests that the digital gold investment adoption process may operate through direct utilitarian evaluation (performance expectancy, risk, value, facilitating conditions) rather than through attitude formation as a prerequisite to intention.

This study examined behavioral intention to adopt digital gold investment apps using an extended UTAUT framework. Results show that Performance Expectancy, Facilitating Conditions, and Perceived Risk are the main drivers of Behavioral Intention, while effort expectancy, social influence, and perceived value are less influential.

Performance Expectancy has the strongest positive effect on intention, aligning with previous UTAUT studies (Venkatesh et al., 2003, 2012). Facilitating Conditions also matter, as user confidence in resources and support increases adoption. Perceived Risk negatively impacts intention, highlighting security and uncertainty as barriers (Appiah et al., 2025; Nakamura et al., 2019).

Attitude does not significantly predict intention, suggesting users rely more on cognitive assessments of usefulness and readiness. Price Value shapes Attitude but does not directly affect intention unless paired with high performance expectancy and support.

These findings highlight the importance of context-specific perceptions: adoption varies with user characteristics and market maturity. Providers should focus on platform design, education, and risk mitigation, as Attitude and Price Value do not directly or indirectly influence intention.

Cognitive and contextual factors shape digital gold adoption. These insights can help providers, policymakers, and researchers develop more effective strategies for digital investment technologies.

CONCLUSION

This study examined the determinants of digital gold adoption using an extended UTAUT model based on the Questionnaire dataset. The findings reveal that Performance Expectancy, Facilitating Conditions, and Perceived Risk are the most influential predictors of Behavioral Intention, whereas Attitude and Price Value do not directly influence intention. Furthermore, Attitude does not mediate any relationship between the constructs and Behavioral Intention. These results highlight the importance of cognitive and contextual evaluations in shaping users' adoption decisions within digital gold investment platforms. The study provides theoretical and practical insights that can guide platform providers, policymakers, and researchers in developing more effective strategies to promote the adoption of digital investment technologies. The empirical results contribute to extending and refining UTAUT-based adoption theories in several key ways. First, the nonsignificant role of Attitude in predicting Behavioral Intention challenges the notion that it serves as a central mediator in fintech adoption. The questionnaire results dataset shows that Attitude does not mediate any relationships between the exogenous constructs and Behavioral Intention. This indicates that the traditional assumption of Attitude as a critical psychological conduit may not hold across all digital financial product contexts. Second, the negative and significant effect of Perceived Risk provides additional theoretical clarity regarding the role of risk perceptions in investment-related technology adoption. While past research has yielded mixed results, the findings here strengthen the argument that users engage in a risk–benefit evaluation before forming behavioral intentions, particularly in financial domains characterized by uncertainty and asset value fluctuations. Third, the results emphasize the direct role of Performance Expectancy and Facilitating Conditions, reaffirming core UTAUT assumptions while illustrating their applicability in modern fintech investment systems. The strong predictive power of the model, as reflected in the R^2 value of 0.865 for Behavioral Intention, also demonstrates that the extended UTAUT framework remains robust in explaining technology adoption decisions, even when the mediating role of Attitude is absent.

From a managerial perspective, the findings from the Questionnaire result dataset provide actionable implications for digital gold providers, app developers, and investors. First and foremost, enhancing Performance Expectancy should be a top priority. Platforms must clearly communicate the tangible benefits of digital gold investments, such as long-term value preservation, inflation hedging, and portfolio diversification. Demonstrating these advantages through tutorials, performance dashboards, and predictive tools may strengthen users' perceptions of usefulness. Second, the significant role of Facilitating Conditions underscores the necessity of reliable infrastructure and accessible support systems. Providers should ensure a smooth onboarding experience, offer intuitive user interfaces, and maintain comprehensive FAQs, chat support, and educational materials to support novice investors. Enhancing system stability, improving transaction transparency, and optimizing platform compatibility across devices can further strengthen facilitating conditions. Third, the negative influence of Perceived Risk indicates that reducing user concerns is essential for increasing adoption. Providers should proactively highlight security measures, including data encryption, regulatory compliance, insurance coverage, and risk management procedures. Ensuring transparent communication about the safety of the digital gold ecosystem can help alleviate user apprehensions. Finally, the nonsignificant role of Attitude and Price Value suggests that

marketing campaigns focused solely on improving user sentiments or offering low fees may not translate effectively into adoption behavior. Instead, strategies must prioritize functional performance, reliability, and risk mitigation.

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