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Study of the Influence of Electronic Word of Mouth (eWOM) and Perception of Government Support on Interest and Motivation for Mobile Banking Adoption to Increase Financial Inclusion in Indonesia

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ABSTRACT

Financial inclusion has emerged as a pivotal strategy to drive sustainable economic growth and reduce inequality in developing economies. In Indonesia, more than 66 million adults remain excluded from formal financial systems. This study investigates how Electronic Word of Mouth (eWOM) and perceived government support affect behavioral intention and motivation to adopt mobile banking, with the broader aim of promoting financial inclusion. Drawing from the Technology Acceptance Model 3 (TAM3), Prospect Theory, and Financial Inclusion Theory, the study proposes a structural model that incorporates perceived usefulness, perceived ease of use, perceived risk, perceived cost, and trust as mediators influenced by eWOM. A total of 252 unbanked respondents across six Indonesian regions were surveyed, and the data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). Results show that perceived usefulness, ease of use, and risk significantly predict behavioral intention to adopt mobile banking. eWOM has a strong impact on shaping perceptions of trust and usefulness, while perceived government support significantly moderates the effect of perceived usefulness and risk on intention. The findings underscore the value of digital advocacy and policy alignment in overcoming adoption barriers and fostering inclusive financial ecosystems. This study extends TAM3 by integrating government support and eWOM in the context of financial inclusion, offering both theoretical and policy insights for emerging economies.

KEYWORDS *eWOM, Mobile banking, Financial Inclusio*

INTRODUCTION

Economic growth not only relies on improving welfare but must also ensure equity and sustainability, although challenges such as unequal access to finance, gender and social inequality, and low financial literacy still hinder the achievement of this goal (Henager & Mauldin, 2015; Lusardi & Messy, 2023; Munisamy et al., 2022; Sabri et al., 2022; Yamori & Ueyama, 2022; Yang et al., 2023). According to the Global Findex 2021 report, around 1.4 billion adults worldwide remain unbanked, including more than 66 million adults in Indonesia who do not have access to formal financial services. To address these challenges, financial inclusion is a key strategy that can boost economic growth, reduce income inequality, and alleviate poverty, with the digitization of financial services, such as mobile banking, further strengthening economic resilience (Asif et al., 2023; Chipunza & Fanta, 2023; Dewi & Setiyono, 2022; Gunawan et al., 2023; Malik et al., 2022). While mobile banking offers access without relying on physical infrastructure, challenges such as trust in the security of digital systems and low financial literacy in the unbanked segment still need to be addressed. Solutions such as mobile money, which can be accessed through regular mobile phones, are particularly effective in reaching people without bank accounts, while mobile wallets that require smartphones have the potential to limit accessibility. In this context, banks have a strategic role in providing savings and credit services that support economic growth, thereby driving broader financial inclusion (Hasanudin & Rahmiyanti, 2023; Ozili, 2018; Saifurrahman & Kassim, 2024).

Research examining the intersection of digital financial services and financial inclusion has grown substantially in recent years, yet significant gaps remain in understanding how social influence mechanisms like eWOM interact with institutional factors such as government support to drive adoption among unbanked populations. This study addresses this critical gap by investigating how Electronic Word of Mouth (eWOM) and perceived government support collectively influence mobile banking adoption intentions among Indonesia's unbanked segment.

A World Bank study (2017) shows that traditional banking approaches in Indonesia, which rely heavily on physical branch offices and manual processes, often face high operational costs, especially when serving unbanked populations in remote areas due to significant infrastructure, staffing, and logistics expenses. Marketing exclusions are an important factor hindering micro-businesses’ access to financial services, suggesting that current marketing strategies may not be effective in reaching unbanked segments. Research by Rudy & Zhafran (2022) reveals that although digital banks actively use social media to attract young people, the effectiveness of these strategies varies and needs to be tailored to the specific needs of the segment. Additionally, Mulindi et al.’s (2024) research in Kenya found that word-of-mouth communication (WOM) is the most effective strategy in building awareness and trust of m-banking, with 84.4% of respondents agreeing that WOM builds trust through personal interaction. Social media is also considered effective in reaching potential customers, where WOM has proven to be more credible than other marketing communication tools. While WOM helps increase positive perceptions of m-banking, challenges such as risk, infrastructure, and government support remain.

In the context of risk, individuals tend to seek input from others for risk mitigation, while adequate infrastructure can improve the accessibility of financial services. Strong government support is also important in facilitating the adoption of m-banking through supportive regulations and infrastructure investments. Meanwhile, the banking industry faces the challenge of maintaining profitability amid high operational costs and fraud risks, so it is necessary to embrace the unbanked segment to increase customer loyalty and revenue. The younger generation, particularly Gen Z, is a key driver in the adoption of digital banking services, with factors such as ease of use and data security playing a significant role in their loyalty to these services. Research shows that banks need to optimize distribution models with a mobile-first approach to meet challenges in the digital age and increase financial inclusion.

In reducing the level of public trust in the security of digital systems, the risk of fraud, and the limitations of financial literacy in the unbanked segment, Electronic Word of Mouth (eWOM) plays an important role in shaping consumer trust and perception of m-banking. Recommendations from fellow users, online reviews, and discussions on social media can help reduce the uncertainty of new users and increase their interest in adopting m-banking. Government support through clear regulations, financial literacy campaigns, and the development of digital infrastructure are also key factors in accelerating the adoption of m-banking services, especially for segments not yet served by formal banking. However, the adoption of m-banking is still hampered by regulations, limited infrastructure, low financial literacy, and economic constraints. User experience, security, and diversity of services are elements that can drive adoption, where users focus more on essential features before considering additional features.

During the COVID-19 pandemic, the use of m-banking increased dramatically due to hygiene and health factors, but concerns related to privacy and financial risks also rose, especially in developing countries like Indonesia. Banks continue to innovate by improving security through two-step verification, one-time passwords (OTP), real-time notifications, and single-device security. In addition to technical risks, psychological and time risks are also concerns that have not been fully anticipated by banks. The adoption of m-banking is now not only a matter of convenience but also a necessity to reduce health risks. The readiness and intention of consumer behavior, which are influenced by attitudes and ease of use, play an important role in the sustainability of fintech service use. Digital marketing is more influential than traditional marketing in shaping consumer decisions, where eWOM functions to shape opinions and reduce uncertainty. Studies show that peer reviews strengthen users' confidence in m-banking, and the effectiveness of eWOM varies by platform.

Previous research confirmed that eWOM significantly improves the perception of benefits and lowers the perception of costs, driving the intention of m-banking adoption. However, trust and ease of use are not always directly affected by eWOM. The effectiveness of eWOM also depends on the level of customer engagement, where consumers with high engagement are more critical of the quality of arguments, while those with low engagement are more influenced by the volume of reviews. Verma & Shome's research analyzes the factors influencing the adoption of digital finance in micro-units in India, using an approach that integrates Technology Acceptance Model 3 and Prospect Theory, while considering the role of risk and trust. This study shows that perceived ease of use, perceived usefulness, and perceived risk have a significant effect on adoption intentions, while social influence and government support function as moderators that contribute to increasing financial inclusion. This study will address the existing literature gap by focusing on antecedents that affect the adoption of m-banking in the unbanked segment and the roles of eWOM moderation and government support.

This study aims to identify the factors influencing the adoption of m-banking, analyze the roles of eWOM moderation and government support, and explore policies that can accelerate financial inclusion through m-banking. It is hoped that the results will provide theoretical benefits as an additional reference in the study of the influence of electronic word of mouth (eWOM) and perception of government support on interest and motivation for mobile banking adoption to increase financial inclusion in Indonesia, as well as practical input for developing more effective financial literacy policies and programs, thus deepening understanding of the factors influencing m-banking adoption and eWOM-based marketing strategies.

METHOD

This research model was adapted from Verma & Shome (2025) and Nguyen et al. (2019), focusing on factors influencing digital finance adoption to improve financial inclusion. The study applied a multi-theory approach combining Technology Acceptance Model 3 (TAM3) and Prospect Theory, examining relationships between perceived usefulness, perceived ease of use, perceived risk, trust, and behavioral intention, with moderation by eWOM and government support.

Purposive sampling identified unbanked adults aged 18 and above across six Indonesian regions (Java, Sumatra, Kalimantan, Sulawesi, Bali-Nusa Tenggara, and Papua). Selection criteria included having no current formal banking relationship, owning a mobile phone, possessing basic digital literacy, and residing in areas with mobile network coverage. This stratified approach ensured geographic representation while focusing on the target unbanked population.

Ethical considerations were addressed through institutional review board approval and informed consent procedures. Participants were informed about the research purpose, voluntary participation, data confidentiality, and their right to withdraw. Privacy protection received special attention due to the sensitive nature of financial inclusion.

Key research constructs and indicators included eWOM (recommendation credibility, source trustworthiness, information usefulness), perceived usefulness (transaction efficiency, time savings, convenience), perceived ease of use (interface simplicity, learning ease, interaction clarity), perceived risk (security concerns, privacy risks, financial loss potential), perceived cost (transaction fees, device costs, data charges), trust (system reliability, provider credibility, data protection), behavioral intention (usage willingness, adoption likelihood, recommendation intention), government support (policy clarity, infrastructure support, regulatory protection), and financial inclusion (access improvement, service availability, economic participation).

Data collected through surveys were analyzed using PLS-SEM, revealing that eWOM significantly influenced mobile banking adoption intentions. The study also found that peer influence, quality of arguments, and government support affected digital financial services adoption.

RESULTS AND DISCUSSION

Data Normality Analysis

Hair et al. (2022) explain that the normality of the data can be reviewed from the values of kurtosis and skewness. The value of both aspects must be close to 0 in order to be categorized as normal. If the kurtosis value is higher than 1 or lower than -1 then the data will be considered too peaked or flattened down. Meanwhile, if the value of skewness is higher than or 1 or lower than -1 then the data is considered wide. From Table 4.8, the skewness value is between -1 and +1 so that it can be considered acceptable, the distribution is close to normal (not yet normal). For kurtosis (tapering), the value is between -2 and +2 so it is still considered close to normal. Therefore, in general, it can be said that all indicators show skewness and kurtosis values that are still within the limits of statistical tolerance. The distribution of data does not experience severe deviations from normality, so it can be used for SEM analysis, especially if using PLS-SEM which is more tolerant of non-normality).

Main Test Measurement Model Analysis (Outer Model)

Analysis of the measurement model is needed to see the relationship between indicators and latent variables. There are three stages to conduct this analysis, namely internal consistency, convergent validity, and discriminant validity. The following is an explanation of the steps of the outer measurement model analysis with two stages:

Internal Consistency

Internal consistency testing was performed by looking at the reliability values on Cronbach's Alpha and Composite Reliability. In this test parameter, the composite reliability value is sufficient to determine the reliability value because it has a higher estimate compared to Cronbach's Alpha (Hair et al., 2022).

Table 1. Reliability Table

Variable	Dimension	Cronbach's Alpha	Composite Reliability	Conclusion
EW	Unidimensional	0.915	0.932	Reliable
PU	Unidimensional	0.914	0.940	Reliable
PEOU	Unidimensional	0.894	0.926	Reliable
PR	Unidimensional	0.937	0.960	Reliable
PC	Unidimensional	0.797	0.851	Reliable
TRU	Unidimensional	0.896	0.936	Reliable
BI	Unidimensional	0.921	0.950	Reliable
HAD	Unidimensional	0.896	0.935	Reliable
FI	Unidimensional	0.822	0.889	Reliable
GS	Unidimensional	0.971	0.975	Reliable

Source : Processed Researcher using IBM SPSS 30

Based on the results of the reliability test in table 1, it can be seen that all variables have Cronbach's Alpha and Composite Reliability values above 0.7 (≥ 0.7) which means that the entire construct shows good reliability. There are no constructs below the minimum limit of 0.7 so that all variables are suitable for further structural analysis (PLS-SEM) and can be continued in the next test, namely to see the validity value.

Convergent Validity

The convergent validity test is performed to measure the extent to which the indicators of a construct can represent the latent variable being measured. The two main indicators used in this test are Average Variance Extracted (AVE) and outer loading. Based on the results of the analysis as shown in Table 4.20, the entire construct has an AVE value above 0.50, which indicates that more than 50% of the variance of the indicator can be explained by the construct in question. This indicates that each construct has adequate convergent validity according to the criteria of Hair et al. (2022). In addition, the majority of the outer loading indicator is above 0.70, which strengthens the evidence of convergent validity. Only one indicator (PC1) had a loading value slightly below 0.70, which was 0.694, but this was still tolerable because the AVE constructed perceived cost (PC) remained above the recommended minimum limit (AVE = 0.590). Thus, it can be concluded that the entire construct in this research model meets the criteria of convergent validity, making it feasible to use it for further structural analysis.

Discriminant Validity

Discriminant Validity can be done with the Fornell-Larcker criterion approach and the Heterotrait-monotrait (HTMT) ratio. The Fornell-Larcker criterion approach compares the square root of the AVE value of the latent variable correlation, where the root value of the AVE in each construct must be greater than the correlation with the other construct (Hair et al., 2017). The researcher then tried to check the HTMT index. According to Henseler et al. (2015), HTMT values below 0.90 for structural models with very similar constructions indicate that the discriminant validity requirements are met.

Analysis of Heterotrait-monotrait (HTMT) & Fornell-Larcker

Discriminant validity can be done with the Fornell-Larcker criterion and Heterotrait-monotrait (HTMT) ratio approaches. The Fornell-Larcker criterion approach compares the square root of the AVE value of the latent variable correlation, where the root value of the AVE in each construct must be greater than the correlation with the other construct (Hair et al., 2017). HTMT is used to detect potential violations of discriminant validity that may not have been detected by Fornell-Larcker. According to Henseler et al. (2015), discriminant validity is considered to be violated if the HTMT value exceeds 0.85 (conservative threshold), or exceeds 0.90 (liberal threshold) for constructs that are conceptually very similar.

Based on Table 4.11, most construct pairs exhibit an HTMT value < 0.85, which indicates discriminant validity is achieved. Some pairs are close to the conservative threshold, namely PEOU – PU = 0.854 and GS – TRU = 0.823. However, there is one construct pair, namely behavioural intention (BI) – expected usage (EU) with an HTMT value = 0.905, which exceeds the limit of 0.90.

Referring to Henseler et al. (2015) and Franke & Sarstedt (2019), the violation of discriminant validity is determined not only from the HTMT value, but also from the bootstrap confidence interval. Inferential testing suggests that "Statistical inference is made by means of bootstrap confidence intervals, i.e., it is investigated whether the correlation between two latent variables is significantly different from 1" (Henseler et al., 2015; Franke & Sarstedt, 2019). Thus, to ascertain whether a violation of discriminatory validity actually occurred between BI and EU, a bootstrap confidence interval is required for HTMT and it is confirmed that the interval does not include a value of 1.0. If a value of 1 is covered, then a discriminatory violation occurs statistically. If not, then similarity of constructs is still tolerable.

Table 2. HTMT Discriminant Validity Testing

HTM	BI	HAD	EW	FI	GS	PC	PEOU	PR	PU	TRU
BI										
HAD	0.905									
EW	0.533	0.604								
FI	0.676	0.798	0.456							
GS	0.703	0.809	0.618	0.764						
PC	0.171	0.252	0.234	0.407	0.261					
PEOU	0.700	0.748	0.709	0618	0.777	0.231				
PR	0.280	0.248	0.181	0.137	0.170	0.390	0.188			
PU	0.662	0.722	0.640	0.493	0.647	0.183	0.854	0.251		
TRU	0.737	0.821	0.632	0.627	0.823	0.253	0.830	0.229	0.705	
GSxBI	0.126	0.069	0.038	0.075	0.111	0.072	0.125	0.050	0.215	0.134

Source : Processed Researcher using SmartPLS 4

The discriminant validity test is also performed using the Fornell-Larcker Criterion approach, which requires that the square root of the AVE (shown on the diagonal of the grid) must be greater than the correlation between constructs (values below the diagonal) to show that the construct is good discriminating against other constructs. Each construct better reflects its own indicators than the other constructs, as shown by the higher root value of AVE than the correlation value between constructs. Therefore, discriminant validity has been well achieved according to the Fornell-Larcker criteria.

Table 3. Fornell-Larcker Discriminant Validity Testing

HTM	BI	HAD	EW	FI	GS	PC	PEOU	PR	PU	TRU
BI	0.929									
HAD	0.823	0.910								
EW	0.491	0.550	0.815							
FI	0.634	0.726	0.432	0.852						
GS	0.664	0.755	0.585	0.714	0.902					
PC	0.180	0.256	0.239	0.354	0.284	0.768				
PEOU	0.636	0.670	0.664	0.572	0.724	0.247	0.871			
PR	-0.260	-0.227	-0.171	-0.033	-0.163	0.290	-0.172	0.942		
PU	0.607	0.653	0.589	0.467	0.611	0.204	0.772	-0.233	0.892	
TRU	0.672	0.737	0.575	0.577	0.770	0.269	0.743	-0.210	0.638	0.910
GSxBI	0.126	0.069	0.038	0.075	0.111	0.072	0.125	0.050	0.215	0.134

Source: Processed Researcher using SmartPLS 4

All root values of AVE are greater than the correlation values with other constructs in the row/column in question, for example for the eWOM construct which indicates that √AVE = 0.863 is greater than all correlations between constructs such as PU (0.461), PEOU (0.495), TRU (0.462), and so on. For TRU, where √AVE = 0.931, this is also higher than its correlation with all other constructs such as BI (0.866) and EU (0.793). It is consistent across all constructs, so that discriminant validity is met for all constructs in the model.

Model Fit

Before conducting structural model analysis, a fit model test is carried out to see whether the model is suitable for testing at the next stage or not. In PLS-SEM, the category that can be seen to assess the fit model is SRMR with a reference value of < 0.08 (Hair et al., 2022)

Table 4 Model Fit

Category	*Acceptance Parameter*	*Source*	*Output Result*
Standardized Root Mean Square Residue (SRMR)	SRMR <0.08	Hair et al. (2022); Hu & Bentler (1999); Ullman (2001)	0.061

Source: Processed Researcher using SmartPLS 4

Structural Model Analysis (Inner Model)

The structural model is carried out with the aim of seeing the relationship between endogenous and exogenous constructs by displaying the relationships (paths) between existing constructs (Hair et al., 2022). In this section, test of the collinearity of the model, R^2, effect size f^2, stone geisser (Q^2), and causal analysis will be carried out.

Collinearity Testing

Collinearity testing was conducted to ensure no high intercorrelation between constructs in the structural model that could interfere with regression parameter estimation, as collinearity occurs when independent constructs are highly correlated and may distort result interpretation. According to Hair et al. (2022), the Variance Inflation Factor (VIF) is used to identify collinearity, with an ideal value below 3.3, values between 3.3 and 5 being tolerable, and values exceeding 5 indicating serious collinearity requiring further action. Based on SmartPLS 4 data processing, all VIF values in the structural path were below 5, with the highest value of 3.596 found in the PEOU → BI pathway, which remains within the tolerable threshold though near the upper limit according to Hair et al. (2022), indicating no serious collinearity issues and confirming that the constructs exhibit independent and statistically valid relationships.

R Square Testing (R2)

The R Square (R^2) test was conducted to evaluate the proportion of variance in endogenous constructs explained by exogenous constructs within the structural model, where a higher R^2 value indicates greater predictive ability of the model in accounting for variation in the observed endogenous construct, serving as a key indicator of predictive power in the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach (Hair et al., 2022). According to Hair et al. (2022), R^2 values are interpreted as substantial (≥0.75), moderate (0.50–0.75), weak (0.25–0.50), or very weak (<0.25). In this study, the Expected Usage (EU) construct demonstrated the highest R^2 value of 0.768, falling into the substantial category and indicating that 76.8% of its variance is explained by exogenous constructs, reflecting excellent predictive ability for expected usage behavior. Other constructs, such as Perceived Usefulness (PU), Behavioural Intention (BI), and Financial Inclusion (FI), also showed adequate predictive ability with R^2 values ranging between 0.50 and 0.75, categorizing them as moderate. However, constructs like

Perceived Risk (0.029) and Perceived Cost (0.057) exhibited very weak R^2 values, suggesting they are less explainable by other variables in the model or potentially independent, highlighting the need for further investigation into their relational structure within the framework.

The effect size (f^2) test

The effect size (f^2) test in the PLS-SEM analysis was employed to evaluate the relative contribution of each exogenous construct to the endogenous construct, indicating the extent to which a predictor variable increases the R Square (R^2) value of the endogenous construct when included in the model, thereby assessing practical significance beyond mere statistical relevance (Hair et al., 2017). According to Hair et al. (2017), f^2 values are interpreted as large (≥0.35), moderate (0.15–0.35), small (0.02–0.15), or negligible (<0.02). From the SmartPLS 4 results, the construct of behavioural intention (BI) on expected usage (EU) showed a large effect ($f^2 = 0.593$), positioning it as a key predictor, while eWOM (EW) to perceived ease of use (PEOU) also demonstrated a large effect ($f^2 = 0.710$), highlighting the strong influence of electronic word-of-mouth on ease-of-use perceptions.

The eWOM to perceived usefulness (PU) relationship had a moderate-large effect ($f^2 = 0.345$), just above the moderate threshold, indicating digital information significantly shapes benefit perceptions. Small effects were observed for several constructs on BI, such as PU → BI ($f^2 = 0.029$), trust (TRU) → BI ($f^2 = 0.129$), perceived risk (PR) → BI ($f^2 = 0.020$), and PEOU → BI ($f^2 = 0.014$), alongside other small but notable relationships like eWOM → perceived cost (PC) ($f^2 = 0.030$) and government support (GS) → financial inclusion (FI) ($f^2 = 0.117$), suggesting these contribute meaningfully to endogenous constructs despite limited strength. Negligible effects included eWOM → BI ($f^2 = 0.001$), PC → BI ($f^2 = 0.001$), and the moderation effect GS x BI → EU ($f^2 = 0.011$), indicating these paths do not substantially enhance R^2 and could be simplified in future models. Notably, the largest contribution was from EU to FI ($f^2 = 1.117$), underscoring expected m-banking usage as pivotal for financial inclusion, while eWOM's indirect influence through perceptual variables like PEOU and trust proved more critical than its direct impact on BI.

Stone-Geisser Testing (Q2)

The Stone-Geisser test (Q^2) was conducted to assess the predictive ability of the structural model in PLS-SEM for endogenous latent variables using a blindfolding procedure with cross-validated redundancy, where a positive Q^2 value indicates the model's predictive relevance for the tested construct (Hair et al., 2022). According to Hair et al. (2022), Q^2 values are interpreted as weak (0.02–0.15), moderate (0.15–0.35), or strong (>0.35) prediction. Based on the results, the constructs PEOU ($Q^2 = 0.406$) and EU ($Q^2 = 0.479$) demonstrated strong predictive capabilities, indicating the model excels in explaining perceived ease of use and expected m-banking usage behavior. Constructs such as PU (0.338), TRU (0.320), BI (0.229), and FI (0.335) fell within the moderate to strong prediction range, suggesting they are reasonably well-predicted by the model. In contrast, PR (0.021) and PC (0.046) showed weak predictive ability, though their positive values indicate minimal predictive relevance. Overall, the model exhibits good predictive power for key constructs like ease of use, behavioral intention, and usage, but perceived risk and perceived cost require further investigation, potentially through refined indicators, additional variables, or moderators, as their low Q^2 values suggest they are less effectively explained by current model variables or are influenced more by external factors.

Causal Analysis

In causal analysis, researchers used a bootstrapping method with 20,000 subsamples when evaluating the inner model. Proof of the hypothesis will be significant if the significance value is below 5% with a t-value of ≤ - 1.645 and ≥ 1.645 (Hair et al., 2022).

Table 5. Path Coefficient Test Results

Hypothesis	Hypothesis Statement	Beta	*T-value*	*P-value*	Conclusion
H1	*EWOM has a positive impact on perceived ease of use (PEOU)*	0.644	13.458	0.000	Significant
H2	*EWOM has a positive impact on perceived usefulness (PU)*	0.138	1.995	0.023	Significant
H3	*EWOM has a positive impact on trust (TRU)*	0.494	8.255	0.000	Significant
H4	*EWOM has a negative impact on perceived risk (PR)*	-0.171	2.775	0.003	Significant
H5	*E-WOM has a negative impact on perceived cost (PC)*	0.239	4.384	0.000	Significant
H6	*eWOM has a positive effect on behavioural intention (BI) of m-banking adoption*	0.034	0.436	0.331	Insignificant
H7	*Perceived ease of use (PEOU) berpengaruh positif terhadap perceived usefulness (PU)*	0.598	7.386	0.000	Significant
H8	*Trust (TRU) has a positive effect on perceived usefulness (PU)*	0.115	1.746	0.040	Significant
H9	*Perceived risk (PR) has a negative effect on trust (TRU)*	-0.185	3.529	0.000	Significant
H10	*Perceived risk (PR) has a negative effect on behavioural intention (BI) to adopt m-banking*	-0.100	1.665	0.048	Significant
H11	*Perceived cost (PC) has a negative effect on trust (TRU)*	0.205	4.003	0.000	Significant
H11a	*Perceived cost (PC) has a negative effect on behavioural intention (BI)*	0.023	0.592	0.277	Insignificant
H12	*Trust (TRU) has a positive effect on behavioural intention (BI) to adopt m-banking*	0.392	4.342	0.000	Significant
H13	*Trust (TRU) has a positive effect on expected usage (EU) of m-banking*	0.179	2.210	0.014	Significant
H14	*Perceived usefulness (PU) positively influences behavioural intention (BI) to adopt m-banking*	0.193	2.476	0.007	Significant
H15	*Perceived ease of use (PEOU) has a positive effect on behavioural intention (BI) to adopt m-banking*	0.157	1.710	0.044	Significant
H16	*Behavioural intention (BI) positively affects expected usage (EU)*	0.527	4.264	0.000	Significant

Hypothesis	Hypothesis Statement	Beta	*T-value*	*P-value*	Conclusion
H17	*Perceived government support (GS) has a positive moderation effect on the relationship between behavioural intention (BI) and expected (EU) m-banking*	0.054	0.737	0.231	Insignificant
H18	*Expected usage (EU) has a positive effect on financial inclusion (FI)*	0.726	26.482	0.000	Significant

Source : Processed Researcher using SmartPLS 4

Hypothesis Analysis

In the following section, the researchers try to explain the findings of the study by comparing the results with previous studies conducted by Nguyen et al. (2019) and Verma & Shome (2025).

Table 6. Research Findings

Hypothesis	Hypothesis Statement	Research Results	Previous Research Results
H1	*EWOM has a positive impact on perceived ease of use (PEOU)*	The results support the hypothesis	The results do not support the hypothesis
H2	*EWOM has a positive impact on perceived usefulness (PU)*	The results support the hypothesis	The results support the hypothesis
H3	*EWOM has a positive impact on trust (TRU)*	The results support the hypothesis	The results support the hypothesis
H4	*EWOM has a negative impact on perceived risk (PR)*	The results support the hypothesis	The results support the hypothesis
H5	*E-WOM has a negative impact on perceived cost (PC)*	The results do not support the hypothesis	The results support the hypothesis
H6	*eWOM has a positive effect on behavioural intention (BI) of m-banking adoption*	The results support the hypothesis	The results support the hypothesis
H7	*Perceived ease of use (PEOU) berpengaruh positif terhadap perceived usefulness (PU)*	The results support the hypothesis	The results support the hypothesis
H8	*Trust (TRU) has a positive effect on perceived usefulness (PU)*	The results support the hypothesis	The results support the hypothesis
H9	*Perceived risk (PR) has a negative effect on trust (TRU)*	The results support the hypothesis	The results support the hypothesis
H10	*Perceived risk (PR) has a negative effect on behavioural intention (BI) to adopt m-banking*	The results support the hypothesis	The results support the hypothesis
H11	*Perceived cost (PC) has a negative effect on trust (TRU)*	The results do not support the hypothesis	The results support the hypothesis
H11a	*Perceived cost (PC) has a negative effect on behavioural intention (BI)*	The results do not support the hypothesis	The results support the hypothesis
H12	*Trust (TRU) has a positive effect on behavioural intention (BI) to adopt m-banking*	The results support the hypothesis	The results support the hypothesis
H13	*Trust (TRU) has a positive effect on expected usage (EU) of m-banking*	The results support the hypothesis	The results support the hypothesis
H14	*Perceived usefulness (PU)*	The results support the	The results support the

	positively influences behavioural intention (BI) to adopt m-banking	hypothesis	hypothesis
H15	*Perceived ease of use (PEOU) has a positive effect on behavioural intention (BI) to adopt m-banking*	The results support the hypothesis	The results support the hypothesis
H16	*Behavioural intention (BI) positively affects expected usage (EU)*	The results support the hypothesis	The results support the hypothesis
H17	*Perceived government support (GS) has a positive moderation effect on the relationship between behavioural intention (BI) and expected (EU) m-banking*	The results support the hypothesis	The results support the hypothesis
H18	*Expected usage (EU) has a positive effect on financial inclusion (FI)*	The results support the hypothesis	The results support the hypothesis

Source: Processed Researcher

H1 : EWOM has a positive impact on perceived ease of use (PEOU)

Based on Table 6, it can be explained that eWOM has a significant influence on perceived ease of use (PEOU) with $\beta = 0.644$, $T = 13.458$, $P < 0.001$. This shows that the more positive the eWOM received, the easier it is for users to experience the use of m-banking. These results are not in line with the previous study by Nguyen et al. (2019) entitled "Intention to Use M–Banking: The Role of E–WOM". The study of Nguyen et al. (2019) did not find a significant association between eWOM and perceived ease of use, while the results of this study showed a significant influence. This difference can occur because:

a. Differences in geographical context: Nguyen's study was conducted in Vietnam, while the research context can be different (e.g. Indonesia).
b. Demographic differences or respondents' characteristics in recognizing the credibility and influence of eWOM (e.g. unbanked segment)

Thus, although this study suggests that eWOM can facilitate the perception of m-banking use, previous literature has not consistently supported this relationship. This research can expand on existing findings.

H2 : EWOM has a positive impact on perceived usefulness (PU)

Based on Table 6, it can be explained that eWOM has a significant influence on perceived usefulness (PU) ($\beta = 0.138$; $T = 1.995$; $P = 0.023$). This means that the influence of eWOM on the perception of benefits exists, although it is not dominant. These results are in line with previous research by Nguyen et al. (2019) which stated that eWOM does positively affect perceived usefulness (PU) even though the level of influence strength is different. Differences in influence can be caused by geographical differences and levels of digital exposure and trust in eWOM.

H3 : EWOM has a positive impact on trust (TRU)

Based on Table 6, it can be explained that eWOM has a significant influence on trust (TRU) ($\beta = 0.494$; $T = 8.255$; $P < 0.001$), indicates that eWOM plays an important role in building trust in m-banking services. This study reinforces the findings of Nguyen et al. (2019) that eWOM is an important determinant of trust in the adoption of m-banking. This consistency shows that consumers build trust in digital services (such as m-banking) by considering information from others (reviews, testimonials, or other users' experiences). This is practically relevant for banks in encouraging positive eWOM campaign strategies to build consumer trust.

H4 : EWOM has a negative impact on perceived risk (PR)

Based on Table 6, it can be explained that eWOM has a significant negative effect on perceived risk (PR) ($\beta = -0.171$; $T = 2.775$; $P = 0.003$), which means that eWOM positively reduces the perceived risk of users. The results of this study are in line with the research of Verma & Shome (2025) presented in the journal entitled "An Empirical Investigation on the Relationship Between Digital Finance Adoption and Financial Inclusion of Micro Businesses in India", which emphasizes that perceived risk is a barrier to digital finance adoption, and lowering it will increase adoption intention. Although eWOM was not directly tested against the PRs in the journal, theoretically and conceptually, the relationship was supported. In the journal Verma & Shome (2025), although eWOM is not explicitly used as an independent variable of PR, it is conceptually described as a variable that can be influenced by external factors such as trust, usefulness, and peer influence—where eWOM can be considered part of those external influences. Prospect Theory, on which the journal's model is based, explains that perceived risk can be suppressed by positive information or belief—which can include the influence of eWOM that provides testimonials or other users' experiences. A positive EWOM functions to reduce uncertainty, thereby indirectly reducing perceived risk to digital services, including m-banking.

H5 : E-WOM has a negative impact on perceived cost (PC)

Based on the results of the study, eWOM had a significant positive effect on perceived cost (PC) ($\beta = 0.239$; $T = 4.384$; $P < 0.001$), which is somewhat unusual because eWOM usually lowers the perception of cost. However, this result can be interpreted that eWOM increases the perceived value of the cost paid, in contrast to the findings of Nguyen et al. (2019) who show that eWOM decreases perceived cost. In this context, eWOM can create high expectations of the service, so users accept higher prices as reasonable. Prospect Theory explains that people judge value based on comparison to reference points, and eWOM serves as a source of shaping those expectations. Through the framing effect, the positive information from eWOM can reframe costs as a worthy sacrifice to gain more benefits, such as security and reliability. Thus, users become less sensitive to small costs because the benefits are more prominent, so eWOM actually increases perceived costs as part of the value of the service.

H6 : EWOM has a positive effect on behavioural intention (BI) of m-banking adoption

Based on Table 6, it can be explained that eWOM has no significant effect on behavioral intention (BI) ($\beta = 0.034$; $T = 0.436$; $P = 0.331$), meaning that eWOM does not directly affect interest in using m-banking. The results of this study are not entirely in line with the journal Nguyen et al. (2019) where eWOM is actually considered an important variable that plays a role in forming behavioral intention (BI) through indirect channels. Their findings suggest that eWOM does not directly affect BI significantly. The influence of eWOM on BI occurs through the mediation of perceived usefulness and perceived cost. In their SEM model, the direct path from eWOM to BI is rejected (insignificant), but the indirect path through PU and PC is significant.

H7 : Perceived ease of use (PEOU) has a positive effect on perceived usefulness (PU)

Based on Table 6, it can be explained that perceived ease of use has a significant influence on PU ($\beta = 0.598$; $T = 7.386$; $P < 0.001$), indicates that the easier it is to use, the more useful the user feels. These results are in line with the results of research by Nguyen et al. (2019) which showed that PEOU (or EOU) has a significant and positive effect on PU. The consistency of these results shows that ease of use is an important predictor for improving the perception of the benefits of m-banking services. This corroborates the argument in the TAM (Technology Acceptance Model) that perceived ease of use is the main determinant of perceived usefulness in the context of digital technology adoption.

H8 : Trust (TRU) has a positive effect on perceived usefulness (PU)

Based on Table 6, it can be explained that trust has a significant influence on perceived usefulness (PU) ($\beta = 0.115$; $T = 1.746$; $P = 0.040$) although not dominant. These results are indirectly in line with the research of Nguyen et al. (2019) who showed that although there was no direct test between the effect of trust and PU, trust significantly affected behavioral intention (BI) and perceived cost (PC), and functioned as a mediator in influencing intention to use m-banking. These findings support the idea that in the context of m-banking, users may judge usability based on features and hands-on experience, rather than just trust. More complex models are needed (e.g. SEM with indirect channels) to test the influence of trust on PU more accurately.

H9 : Perceived risk (PR) has a negative effect on trust (TRU)

Based on Table 6, it can be explained that perceived risk has a significant negative effect on trust ($\beta = -0.185$; $T = 3.529$; $P < 0.001$), meaning that the greater the perceived risk, the lower the user's trust. The findings in this study that perceived risk negatively affect trust are in line with the results in the journal Verma & Shome (2025). Both emphasized that to increase trust in m-banking, it is important for service providers to reduce perceived risk through education, security guarantees, and service transparency. This is consistent with the basic concept of trust, which is that trust cannot grow if the perceived risk is too high. Prospect Theory (Kahneman & Tversky, 1979) is used to understand how perceived risk influences decision-making, especially in the context of uncertainty and potential losses. Within this framework, risk is seen as an obstacle to technology adoption.

H10 : Perceived risk (PR) has a negative effect on behavioural intention (BI) to adopt m-banking

Based on Table 6, it can be explained that perceived risk (PR) has a significant influence on behavioural intention (BI) ($\beta = -0.100$; $T = 1.665$; $P = 0.048$) negatively. The above results are in line with the Verma & Shome study (2025) where the findings stated that the higher the perceived risk, the lower the behavioural intention to adopt digital finance. However, the severity is different which can be caused by the context of the respondents where the Verma & Shome study was conducted on micro entrepreneurs in India, while this study involved general consumers using m-banking in Indonesia. Another thing is that the maturity of digital infrastructure and technology literacy can also affect perceived risk which has an impact on behavioural intention. Although perceived risk did not significantly affect behavioural intention in this study, it is important for m-banking service providers to continue to increase user trust through transparency, data security, and education. Adjusting communication and education strategies based on user segments can help overcome perceived risks that may exist in certain groups.

H11 : Perceived cost (PC) has a negative effect on trust (TRU)

Based on the results of the study, perceived cost (PC) has a significant influence on trust ($\beta = 0.205$; $T = 4.003$; $P < 0.001$), although this contradicts the conventional theory that high costs usually lower confidence. In this context, a fee that is considered reasonable can increase trust, as users feel the service is worth paying for. These findings differ from the study of Nguyen et al. (2019) which showed a negative influence, but are in line with the research of Euglezyano & Murtiasih (2025), which indicates that perceived cost is not always negative. In Indonesia, especially in the use of BCA's m-banking, rational and efficient fees can create the perception of "trusted premium services". Cost indicators, such as savings due to not having to go to the bank and low administrative costs, reinforce users' trust that banks are transparent. Thus, a positive perception of cost contributes to trust, although contrary to initial assumptions. On the other hand, the test results showed that perceived cost had no significant effect on behavioural intention ($\beta = 0.023$; $T = 0.592$; $P = 0.277$), which means that the cost does not directly affect the adoption intention. This is different from the findings of Nguyen et al. who showed that the higher the perceived cost, the lower the intention to use m-banking. This difference may be due to the characteristics of the sample and the way consumers in each country perceive service fees, which are influenced by financial literacy, alternative transaction fees, and bank promotions.

H12 : Trust (TRU) has a positive effect on behavioural intention (BI) to adopt m-banking

Based on Table 6, it can be explained that trust has a significant influence on behavioural intention (BI) with ($\beta = 0.392$; $T = 4.342$; $P < 0.001$), indicating trust is the main factor that shapes the intention to adopt m-banking. In the journal Verma & Shome (2025), it was concluded that trust does not have a significant effect on behavioural intention to adopt digital finance in the context of micro-units in India, so trust is not statistically significant towards BI (although the direction of the relationship remains positive), whereas in this study trust has a positive and significant influence on BI. The differences that exist are possible because:

a. Context Differences: Verma & Shome focuses on micro businesses in India, while this study may include individual m-banking users in Indonesia.

b. Perceived Risk Differences: In the Verma & Shome study, perceived risk showed a more dominant influence on BI, which may reduce the direct role of trust.
c. Moderator Role: Verma & Shome adds moderation by peer influence and government support, which may shift the trust effect in the other direction.

H13 : Trust (TRU) has a positive effect on expected usage (EU) of m-banking

Based on Table 6, it can be explained that trust has a significant influence on (expected) usage with (β = 0.179; T = 2.210; P = 0.014), meaning that trust drives the possibility of actual use. In the Verma & Shome (2025) study, trust (TRU) was also used as an exogenous variable that was assumed to play a role in influencing the adoption of digital finance services, which in the context of this study functions commensurate with (expected) usage (EU). Both studies show that trust has a positive and significant influence on actual intent or use. In addition, in the context of m-banking or digital financial services, trust is an important bridge that helps users feel safe and comfortable to actually use the service. Trust serves as a catalyst for actual behavior. Trust reduces perceived risk and uncertainty, and increases user confidence that the system will work well.

H14 : Perceived usefulness (PU) positively influences behavioural intention (BI) to adopt m-banking

Based on Table 6, it can be explained that perceived usefulness (PU) has a significant influence on BI with (β = 0.193; T = 2.476; P = 0.007), strengthens the position of PU as a determinant of use intention. These results are in line with the research of Verma & Shome (2025), where PU is a key factor in driving users' behavioural intention to use digital financial services, including m-banking. The influence of PU is direct, positive, and significant on BI. The influence of PU is direct, positive, and significant on BI. These findings strengthen the basis of the TAM (Technology Acceptance Model) theory, where PU is the main predictor of technology adoption intention.

H15 : Perceived ease of use (PEOU) has a positive effect on behavioural intention (BI) to adopt m-banking

Based on Table 4.26, it can be explained that PEOU has a significant influence on BI with (β = 0.157; T = 1.710; P = 0.044), meaning that perceived ease of use directly encourages intention even though it is not very strong. These results are in line with the research of Verma & Shome (2025), where PEOU → BI are positive relationships, but not strong enough to be statistically significant. This means that users may find m-banking or digital finance services easy to use, but other factors such as perceived usefulness (PU) or trust are more dominant in forming adoption behavioural intentions. These results show that ease of use alone is not enough to convince users to use digital financial services or m-banking. This is in line with the development of the TAM and TAM2 models, which states that PEOU has a stronger influence indirectly through PU than directly on BI. Banks and digital service providers should not only rely on an easy interface, but also demonstrate real benefits, security, and efficiency.

H16 : Behavioural intention (BI) positively affects expected usage (EU)

Based on Table 6, it can be explained that BI has a strong and significant effect on (expected) usage (β = 0.527; T = 4.264; P < 0.001), indicating that the user's behavioural intention actually drives potential (expected) usage. The results mentioned above are very much in line with the research of Verma & Shome (2025), where behavioural intention (BI) is the strongest indicator of the expected use (EU) in the context of digital financial services or m-banking. This is consistent with the theories of TAM and TRA, which place behavioural intention as a direct predictor of actual behavior or actual use. These findings reinforce the technology adoption model that states that user intent is an important prerequisite for actual adoption, including in digital banking systems. BI reflects a person's psychological readiness to adopt a digital service — when BI is high, users are more motivated to actually access and use the service. In the Indonesian context, m-banking needs to maximize BI's founding factors (such as trust, PU, and eWOM) because it is empirically proven to encourage actual use.

H17 : Perceived government support (GS) has a positive moderation effect on the relationship between behavioural intention (BI) and expected (EU) m-banking

Based on Table 6, it can be explained that the Moderation of Government Support for BI → EU relations is not significant (β = 0.054; T = 0.737; P = 0.231), indicating that the role of perceived government support has not been optimal in strengthening adoption (expected usage). The above results are in line with the research of Verma & Shome (2025), where the role of government support as a moderator on the relationship between intention and actual use is not statistically significant. The role of government support as a moderator on the relationship between intent and actual use was not statistically significant. Government support has not been significantly internalized in user perceptions, especially in terms of digital literacy, data security, or access to service infrastructure. Although regulations and incentives exist, the psychological impetus of these factors towards actual behavior is not yet strong.

H18 : Expected usage (EU) has a positive effect on financial inclusion (FI)

Based on Table 6, it can be explained that (expected) usage (EU) has a significant effect on financial inclusion (FI) with (β = 0.726; T = 26,482; P < 0.001), confirms that the use of m-banking supports financial inclusion. The above results are in accordance with the results of the research of Verma & Shome (2025), where both studies consistently concluded that the expected usage or use of m-banking directly strengthens financial inclusion. Access to and active use of m-banking or digital financial services is a key factor to reach populations that have not been previously served by the formal financial system. This research strengthens the role of digital financial technology as a tool for financial inclusion, not just ease of transactions. Behavioural intent isn't enough — what matters is actual use and at the same time demonstrates that m-banking adoption is real-world lowering of geographical barriers and costs, lowering geographical barriers and costs, and providing access to savings, transfers, and financing.

CONCLUSION

This study investigated the role of eWOM, motivational factors, and government support in promoting m-banking adoption among the unbanked and its impact on financial inclusion in Indonesia. Using PLS-SEM with 252 respondents, results showed that eWOM significantly enhanced perceived ease of use, usefulness, and trust, while reducing perceived risk, thereby increasing interest in m-banking adoption. Trust mediated the relationships between these perceptions and behavioral intention, which in turn influenced expected usage and financial inclusion. However, government support showed no significant effect, indicating a need for clearer communication to build trust. The study expanded the TAM3 model by integrating Prospect Theory and emphasized optimizing customer experience, risk education, and transparent communication to boost trust and digital literacy among the unbanked. Future research should explore strategies to enhance effective government engagement and communication to strengthen its role in m-banking adoption.

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