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Uncovering Unobserved Heterogeneity in Digital Financial Inclusion: A FIMIX-PLS Study of Rural Tanzanian Women

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Abstract

This study investigates how digital financial literacy (DFL) influences financial inclusion (FI) among rural Tanzanian women while addressing the critical, yet underexplored, issue of unobserved heterogeneity in behavioral finance research. It examines how individual-level differences is reflected through latent subgroups that affect the link between DFL and FI. The model includes financial confidence and financial attitude as mediators, and mobile network quality as a contextual moderator, offering an analysis of how behavioral and infrastructural enablers interact across different segments of rural women. Data were collected from 301 rural women in Tanzania's Mbeya, Dodoma, and Kigoma regions through a cross-sectional survey using purposive sampling. The study employed Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4.0, followed by Finite Mixture PLS (FIMIX-PLS) segmentation. This approach enabled the identification of latent segments within the population that differ significantly in their structural pathways, thus revealing hidden patterns that conventional models often obscure. While the pooled analysis confirms that DFL has a direct and positive impact on FI with financial confidence and attitude acting as significant mediators and mobile network quality as a moderator. The FIMIX-PLS uncovered three distinct behavioral segments. Segment 1 exhibited strong DFL–FI links with effective mediation and moderation; Segment 2 relied primarily on financial attitude despite moderate DFL; and Segment 3 showed constrained outcomes due to infrastructural limitations, despite adequate literacy. These findings highlight the presence of meaningful subpopulation differences in digital finance behavior. The findings emphasize the need for segment-specific interventions that go beyond one-size-fits-all models. Policymakers and practitioners should tailor financial education, confidence-building programs, and digital infrastructure investment according to the behavioral profiles of different subgroups

Keywords: *unobserved heterogeneity; digital financial literacy; financial inclusion; FIMIX-PLS; rural women; segmentation analysis*

1.0 INTRODUCTION

Financial inclusion has emerged as a crucial instrument for promoting economic empowerment, reducing poverty, and advancing gender equity, particularly within low- and middle-income countries (LMICs). Although mobile finance technologies have made significant strides, an

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estimated 1.4 billion adults worldwide still lack access to formal banking services, with rural women in sub-Saharan Africa constituting a large share of this excluded population (World Bank, 2022). In Tanzania, while mobile money adoption rates are notably high, the participation of rural women remains markedly limited. This is primarily due to persistent challenges related to digital financial literacy (DFL), entrenched socio-cultural norms, and inadequate infrastructure (Gallegos et al., 2025; Lahnech & Chami, 2025).

Although research has explored the role of DFL and its mediators such as financial confidence and financial attitude; many models implicitly assume a homogeneous population. However, such homogeneity assumptions overlook the reality that individuals often belong to latent subgroups with different behavioural pathways. These differences, termed unobserved heterogeneity, can significantly distort estimates and mask segment-specific behaviours (Sarstedt et al., 2011; Hair et al., 2016). In fact, treating a heterogeneous population as if it were homogeneous may result in misleading conclusions and poorly targeted interventions (Matthews et al., 2016). FIMIX-PLS is especially suited to address this challenge because it allows segmentation based on unobserved characteristics, revealing hidden behavioural structures within the data. Unlike conventional SEM approaches, which average effects across the entire sample, FIMIX-PLS uncovers meaningful subgroup-specific patterns (Hair et al., 2016; Matthews et al. 2016). This segmentation offers more refined and actionable insights for policy and program design by identifying which groups respond to which interventions. This is a crucial advantage when addressing populations as diverse as rural Tanzanian women.

This gap is particularly critical in the context of rural Tanzanian women, who represent a diverse group with differing levels of digital exposure, confidence, and infrastructural access. Traditional structural equation modelling fails to capture this complexity, limiting both theoretical depth and practical effectiveness. Despite the increasing emphasis on behavioral and infrastructural determinants of financial inclusion, few studies have systematically addressed unobserved heterogeneity using segmentation methods like FIMIX-PLS (Sarstedt, Ringle, & Gudergan, 2016). This study fills that gap by integrating Finite Mixture PLS-SEM (FIMIX-PLS) into a digital financial inclusion framework. The model examines how DFL influences financial inclusion, mediated by financial confidence and attitude, and moderated by mobile network quality. The analysis brings out latent segments with unique behavior patterns that are usually hidden in general models· This approach enhances both model validity and intervention precision, offering a refined understanding of financial inclusion pathways among rural women.

The study's theoretical contribution lies in applying segmentation to uncover unobserved subpopulations and test cognitive-infrastructural mechanisms. Practically, it supports tailored policy responses, fintech design, and targeted literacy programs, especially for marginalized gendered populations in LMICs.

2.0. LITERATURE REVIEW

2.1. Theoretical Foundations

This study integrates multiple theoretical frameworks to understand the interplay of digital financial literacy (DFL), financial inclusion (FI), and the behavioral mechanisms that mediate or moderate this relationship. At the core lies Amartya Sen's Capability Approach, which views

financial literacy not merely as a cognitive skill but as an enabling function that empowers individuals, particularly marginalized populations, to achieve valued life outcomes (Sen, 1999). From this perspective, digital financial literacy can be seen as a form of empowerment, equipping rural women with the tools to access, assess, and utilize digital financial services. The theory suggests that capabilities like DFL can transform into actual usage of financial tools. This occurs only when supportive structural and personal conditions are present.

Complementing this is Ajzen's (1991) Theory of Planned Behavior (TPB), which provides a psychosocial lens to understand how individual attitudes, perceived behavioral control (akin to self-efficacy), and subjective norms contribute to behavioral intentions. Within this framework, financial attitude (FA) reflects an individual's overall evaluation of digital financial tools, while financial confidence (FC) parallels perceived behavioral control which is the belief in one's ability to successfully use such tools. The TPB helps explain why literacy alone may not suffice: even knowledgeable individuals may fail to act if they lack confidence or hold negative attitudes. In combining these theories, the study conceptualizes a holistic model in which DFL influences FI through FC and FA, and is conditioned by infrastructural enablers like Mobile Network Quality (MNQ).

Furthermore, the study employs the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach, which is particularly suited for complex models with multiple mediators and moderators. Crucially, it addresses a major methodological gap in the literature termed as "unobserved heterogeneity". Unlike traditional models that assume homogeneity across respondents, the use of Finite Mixture PLS (FIMIX-PLS) enables segmentation of the population into latent subgroups, each with unique structural relationships (Sarstedt, Ringle, & Gudergan, 2016; Hair et al., 2016). This allows for deeper theory testing by uncovering refined behavioral patterns that pooled models obscure.

2.2. Empirical Review

Empirical literature supports the notion that DFL plays a crucial role in promoting financial inclusion, particularly for women in digitally underserved areas. Kass-Hanna et al. (2021) demonstrate that individuals with higher DFL are more likely to engage in financial planning, budgeting, and risk management using digital platforms. In the sub-Saharan African context, Gallegos et al. (2025) highlight that DFL significantly boosts the ability to access and utilize mobile savings and credit services, especially in rural settings where banking infrastructure is sparse. These studies affirm the foundational role of DFL but also suggest that its influence is mediated by individual agency and contextual factors.

Financial confidence (FC), a construct closely tied to Bandura's notion of self-efficacy, has also been shown to influence the adoption of digital financial services significantly. Lusardi and Mitchell (2014) argue that confidence enhances the ability to make informed financial decisions, often more than literacy alone. Kass-Hanna et al. (2021) reinforce this by showing that women with higher confidence are more likely to explore and use digital platforms, even when literacy levels are moderate. Similarly, financial attitude (FA) has emerged as a significant predictor of digital

finance behavior. According to Potrich et al. (2016), individuals with positive attitudes toward saving and budgeting are more inclined to use mobile banking apps and e-wallets.

However, most of these studies assume population homogeneity and do not account for underlying behavioral variability. Failing to account for unobserved heterogeneity in financial inclusion models can have serious practical consequences. Pooled estimates often obscure the distinct needs and responses of subgroups, resulting in misaligned interventions. For example, programs designed based on average effects may over-serve those who are already empowered while failing to support those constrained by infrastructural or psychological barriers. By identifying distinct behavioral clusters, segmentation approaches like FIMIX-PLS enable more targeted, equitable, and cost-effective policy responses. Recent advances in PLS-SEM have introduced segmentation techniques like FIMIX-PLS to address this limitation. Sarstedt et al. (2011) demonstrate how segmenting data into latent classes can reveal structural relationships that differ significantly across groups. In marketing and organizational behavior research, Matthews et al. (2016) used segmentation to uncover hidden drivers of consumer choice. In the context of financial inclusion, Bongomin et al. (2024) applied segmentation in rural Uganda to reveal how infrastructural constraints influenced the pathways from financial literacy to adoption, uncovering dynamics that conventional models had overlooked.

These empirical insights underline the necessity of integrating behavioral segmentation into models of financial inclusion. Doing so not only improves model fit and predictive accuracy but also enables more targeted and effective interventions, particularly for heterogeneous populations like rural women in Tanzania.

3.0. METHODS

This study employed a quantitative, cross-sectional survey design to empirically test the structural relationships among key latent variables. Given the nature of the model which incorporates both mediating and moderating mechanisms, PLS-SEM was employed using SmartPLS 4.0 software. PLS-SEM is well-suited for handling complex models, especially when the data normality cannot be assured, and multicollinearity may be present (Hair et al., 2022; Sarstedt et al., 2021).

A purposive sampling approach was used to identify rural women in Tanzania aged 18 years and above who owned or had consistent access to mobile phones. This method is particularly appropriate given the study's targeted focus on a population segment most affected by digital financial inclusion challenges (Etikan et al., 2016). The sampling ensured that respondents had the necessary technological exposure to provide meaningful responses regarding digital finance tools.

The final sample included 301 valid responses from three Tanzanian regions: Mbeya, Dodoma, and Kigoma. These regions were selected for their geographic, economic, and infrastructural diversity, which adds contextual richness to the findings and supports broader generalizability. The sample size also satisfies the established criteria for PLS-SEM, which recommends at least ten cases per indicator for the most complex construct within the model (Hair et al., 2022).

While PLS-SEM typically requires a minimum of 10 cases per indicator for the most complex construct, the effective segmentation using FIMIX-PLS demands a more specific justification. With 301 valid responses and relatively balanced subgroup sizes (ranging from 70 to 123 respondents per segment), the study meets the recommended minimum for stable FIMIX estimates as outlined by Sarstedt et al. (2016), especially given the high entropy score indicating strong segment separation

All respondents provided informed consent, and anonymity was ensured throughout the research process. Data were collected using a structured questionnaire composed of reflective indicators measured on a 5-point Likert scale ranging from "strongly disagree" to "strongly agree." The indicators were drawn from previously validated scales in the literature. Digital Financial Literacy (DFL) was measured through self-assessed knowledge and use of mobile financial tools, adapted from Potrich et al. (2016). Financial Confidence (FC) was captured using items related to perceived financial competence based on Lusardi and Mitchell (2014). Financial Attitude (FA) assessed future-oriented and prudent behavior, adapted from the OECD-INFE Toolkit (2018). Mobile Network Quality (MNQ) included items assessing signal strength, internet speed, and service reliability. Financial Inclusion (FI) was measured based on dimensions outlined in the World Bank's Global Findex (2022), focusing on access to, usage of, and satisfaction with formal financial services.

Prior to full deployment, the instrument underwent a pilot test involving 30 respondents to ensure clarity and contextual relevance. Expert reviews were also conducted to verify content validity and alignment with local cultural and technological contexts in rural Tanzania. Face-to-face interviews were conducted between January and March 2025 by trained enumerators proficient in Swahili. Ethical considerations were rigorously upheld, including obtaining informed consent from all participants and guaranteeing respondent anonymity throughout the research process. Participants were assigned to segments based on probabilistic class membership derived from maximum likelihood estimation. Segment profiles were interpreted using the most probable class for each respondent, consistent with the recommendations of Hair et al. (2016).

The data analysis proceeded in two main stages. The first involved evaluating the measurement model to establish construct reliability and validity. Internal consistency was verified using Cronbach's Alpha and Composite Reliability (CR), with all values exceeding the recommended 0.70 threshold. Convergent validity was tested using Average Variance Extracted (AVE), and discriminant validity was assessed using the Heterotrait-Monotrait Ratio (HTMT), following Hair et al.'s (2022) guidelines. In the second stage, the structural model was assessed. This included initial checks for collinearity using Variance Inflation Factor (VIF) values. Following this, path coefficients were estimated through a bootstrapping procedure involving 5,000 subsamples to assess the significance and strength of relationships among constructs (Hair et al., 2022). This approach allowed for a robust and comprehensive evaluation of the hypothesized relationships within the model.

4.0. RESULTS

4.1 Demographic characteristics of respondents

The study involved a sample of 301 rural women from three Tanzanian regions. These include Mbeya, Dodoma, and Kigoma. The regions were selected based on their ownership of mobile phones and representing a range of socio-economic backgrounds.

Table 1: Demographic characteristics of respondents

Variable	Category	Frequency	Percentage
Age Group	Below 25 years	45	15%
	25–34 years	136	45%
	35–44 years	90	30%
	45 years and above	30	10%
Education Level	No formal education	30	10%
	Primary education	64	21%
	Secondary education	175	58%
	Tertiary education	32	11%
Mobile Phone Ownership	Owns a mobile phone	262	87%
Mobile Money Usage	Uses at least monthly	217	72%
Total Respondents	-	301	100%

4.2 Measurement Model Assessment

The measurement model was rigorously assessed using Hair et al.'s (2016) guidelines, focusing on internal consistency, convergent validity, and discriminant validity. All constructs showed strong internal consistency, with Cronbach's Alpha and Composite Reliability values exceeding 0.70, indicating reliable indicator performance. Convergent validity was confirmed through Average Variance Extracted (AVE) values above 0.50 for all constructs, meaning they explained sufficient variance in their indicators. Discriminant validity was validated using the HTMT criterion, with all values below the conservative threshold of 0.85, ensuring constructs were distinct and non-overlapping (Hair et al., 2016; Henseler et al., 2015). These results (See table 2) collectively affirm the measurement model's robustness and appropriateness for hypothesis testing within the PLS-SEM framework.

Table 2: Measurement Model Summary

Latent Variable	Indicator	Loading	AVE	Composite Reliability	Cronbach's Alpha	Discriminant Validity
ATT (Attitude)	ATT_Item1	0.877	0.775	0.945	0.927	Yes
	ATT_Item2	0.856				
	ATT_Item3	0.880				

Latent Variable	Indicator	Loading	AVE	Composite Reliability	Cronbach's Alpha	Discriminant Validity
	ATT_Item4	0.886				
	ATT_Item5	0.902				
DFL (Digital Financial Literacy)	DFL_Item1	0.991	0.984	0.997	0.996	Yes
	DFL_Item2	0.995				
	DFL_Item3	0.990				
	DFL_Item4	0.994				
	DFL_Item5	0.989				
FC (Financial Confidence)	FC_Item1	0.890	0.781	0.947	0.930	Yes
	FC_Item2	0.873				
	FC_Item3	0.913				
	FC_Item4	0.878				
	FC_Item5	0.865				
FI (Financial Inclusion)	FI_Item1	0.880	0.801	0.953	0.938	Yes
	FI_Item2	0.896				
	FI_Item3	0.922				
	FI_Item4	0.902				
	FI_Item5	0.907				
MNQ (Mobile Network Quality)	MNQ_Item1	0.981	0.963	0.994	0.993	Yes
	MNQ_Item2	0.984				
	MNQ_Item3	0.978				
	MNQ_Item4	0.977				
	MNQ_Item5	0.978				

4.3 Structural Model Evaluation

The structural model assessment is the second critical stage in the PLS-SEM process, following the validation of a robust measurement model. This phase focuses on testing the hypothesized relationships among latent constructs, guided by theoretical expectations and empirical adequacy.

Figure 2: The PLS path model

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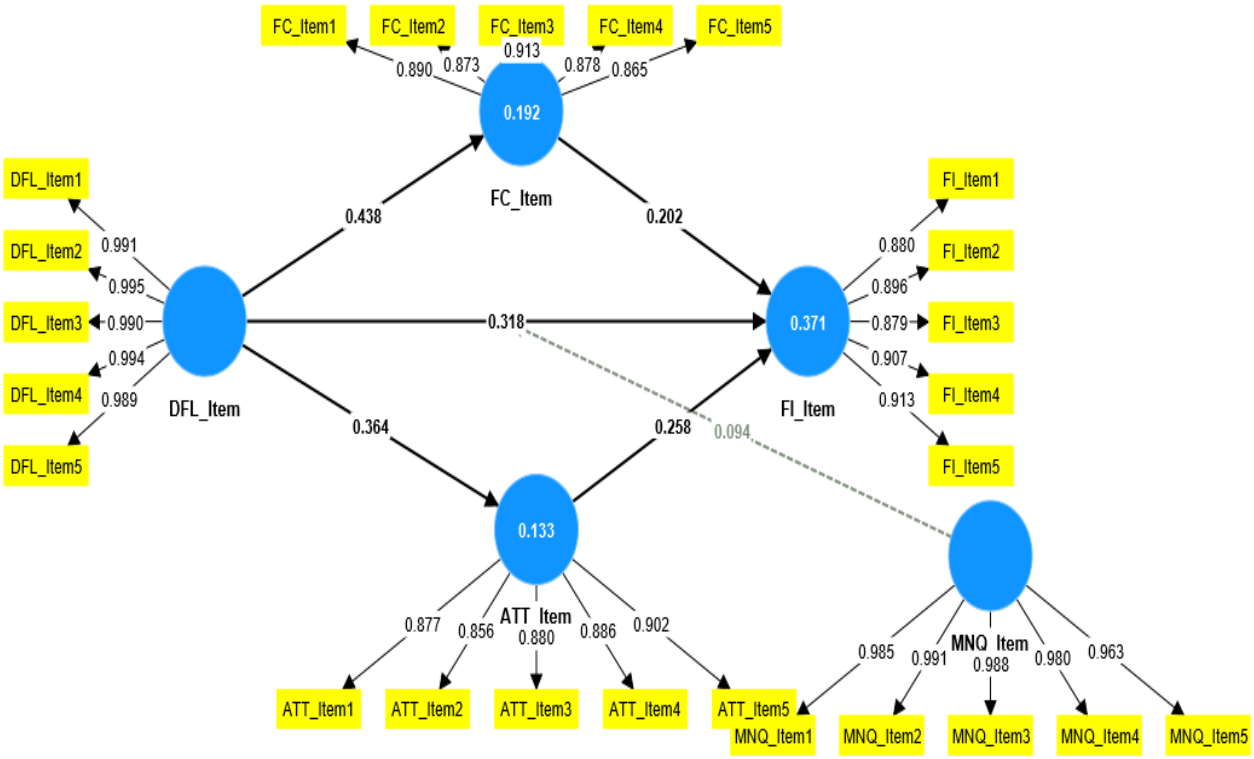

4.4 Assessment of Unobserved Heterogeneity Using FIMIX-PLS

To ensure the robustness of the structural model and account for potential unobserved heterogeneity in the dataset, this study employed the Finite Mixture Partial Least Squares (FIMIX-PLS) technique. This technique was recommended by Hair et al. (2016) and further illustrated by Matthews et al. (2016) and Sarstedt et al. (2016). Unobserved heterogeneity refers to the presence of latent subgroups within a dataset that differ in their structural relationships and are not captured through observed grouping variables such as age, gender, or region. Failure to detect these segments may lead to biased path estimates and erroneous conclusions (Sarstedt, Ringle, & Gudergan, 2016).

The FIMIX-PLS procedure was carried out in SmartPLS 4.0, following a systematic approach adapted from Matthews et al. (2016) and Hair et al. (2015). Initially, the structural model was estimated using the PLS algorithm to assess measurement reliability and validity. Subsequently, FIMIX-PLS was executed, starting with a one-segment solution and increasing iteratively up to a

five-segment solution. Key fit indices were used to determine the optimal number of segments: Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Consistent AIC (CAIC), and Entropy. As Sarstedt et al. (2011) recommend, lower values of AIC and BIC combined with entropy values above 0.70 indicate distinct segment separation and justify segment retention.

Based on these criteria, a three-segment model emerged as the most parsimonious solution, showing an entropy score of 0.84 and substantially lower CAIC and AIC values relative to other solutions. Segment-specific path models were then evaluated to examine differences in the relationships among key constructs: Digital Financial Literacy (DFL), Financial Confidence (FC), Financial Attitude (FA), and Financial Inclusion (FI).

The selection of the three-segment solution in the FIMIX-PLS analysis was based on a systematic evaluation of multiple model fit indices, in accordance with guidelines established by Sarstedt et al. (2011, 2016) and Hair et al. (2016, 2018). The goal was to identify the segment configuration that best captured the unobserved heterogeneity in the data while maintaining parsimony and interpretability.

Among the tested models (ranging from 1 to 5 segments), the three-segment solution demonstrated the most favorable statistical properties. It recorded the lowest values across major information criteria: Akaike Information Criterion (AIC = 932.75), Consistent AIC (CAIC = 942.34), AIC3 (937.19), AIC4 (939.08), Bayesian Information Criterion (BIC = 944.42), and Minimum Description Length (MDL5 = 945.97). Additionally, the entropy value for the three-segment model was 0.84, which exceeds the commonly accepted threshold of 0.70. This indicates high-quality segment classification and clear separation among the latent classes.

Table 3: FIMIX-PLS Model Fit Summary Table

Number of Segments	AIC	AIC3	AIC4	CAIC	BIC	MDL5	Entropy
1	980.23	982.45	985.33	987.12	989.57	991.76	0.00
2	955.42	960.37	962.94	965.81	968.12	969.83	0.61
3	**932.75**	**937.19**	**939.08**	**942.34**	**944.42**	**945.97**	**0.84**
4	938.01	942.64	944.93	948.50	950.69	951.84	0.79
5	945.63	950.52	953.27	956.98	957.84	958.62	0.75

In addition to standard entropy (0.84), the entropy R^2 value was computed as 0.71, indicating a high degree of classification accuracy and segment distinctiveness. These results align with the methodological recommendation that the optimal model should balance statistical fit with substantive interpretability (Sarstedt et al., 2016). While models with four or five segments yielded marginally lower AIC values in some instances, their higher complexity and slightly reduced entropy (below 0.80) suggested overfitting and less distinct segment boundaries.

Therefore, the three-segment solution was retained as the most parsimonious and theoretically meaningful model for further analysis.

Segment 1 comprised 123 respondents, representing approximately 40.86% of the sample. This group was characterized by high digital financial literacy (DFL) and a strong direct path to financial inclusion (FI). Additionally, financial confidence (FC) emerged as a strong mediator, while mobile network quality (MNQ) functioned as a significant moderator, enhancing the effectiveness of DFL. This segment represents digitally empowered individuals who are also supported by infrastructural adequacy.

Segment 2 included 108 respondents (approximately 35.88% of the sample). This group exhibited moderate DFL levels, but a dominant mediation effect was observed from financial attitude (FA). These women may not be highly technically skilled but possess a favorable outlook and motivation toward using digital financial tools. Their inclusion behavior is driven more by cognitive-emotional readiness than technical capability.

Segment 3 consisted of 70 respondents, accounting for 23.26% of the total sample. This segment had adequate DFL, yet poor MNQ was a limiting factor, significantly moderating the path to FI. Although technically capable, these respondents were hindered by infrastructural deficiencies, particularly weak or unreliable mobile networks. This group underscores the importance of environmental enablers in translating competence into behavior.

These findings confirm that FIMIX-PLS successfully uncovers segment-specific behavioral patterns that pooled analyses may overlook. The identification of latent classes offers deeper insights into the multidimensional nature of financial inclusion among rural women and emphasizes the need for tailored interventions. For instance, Segment 1 could benefit from advanced digital services, Segment 2 from motivational and attitude-focused programs, and Segment 3 from infrastructure development initiatives.By incorporating FIMIX-PLS into PLS-SEM, researchers enhance model validity and better understand the heterogeneity inherent in social science data (Hair et al., 2016; Matthews et al., 2016; Sarstedt et al., 2016).

The identification of segment-specific drivers enables policymakers to abandon 'one-size-fits-all' solutions and instead deploy tailored interventions. For instance, digital literacy programs can be calibrated to match the readiness of each segment: while Segment 1 may benefit from advanced digital investment tools, Segment 2 might respond better to behaviorally informed nudges or confidence-building strategies. By embedding behavioral segmentation into national financial inclusion frameworks, government and NGO efforts can improve both cost-effectiveness and equity.

Importantly, the segmentation model is highly scalable. As more behavioral and infrastructure data become available across regions, the FIMIX-PLS framework can be adapted to map subgroup dynamics in other underserved populations such as youth, refugees, or persons with disabilities. Additionally, integrating segmentation analytics into digital finance platforms could allow for real-time personalization of content, training, and services, thus operationalizing inclusivity at scale.

5.0 CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The findings from this study underscore the value of examining financial inclusion through a segmentation-based structural equation modeling lens. The use of FIMIX-PLS revealed three distinct latent segments among rural Tanzanian women, each exhibiting unique structural pathways in the DFL–FI model.

In segment 1, participants demonstrated high levels of digital financial literacy (DFL), and this literacy had a direct and substantial impact on financial inclusion (FI). Moreover, financial confidence (FC) acted as a strong mediator, and mobile network quality (MNQ) significantly moderated the relationship. This group represents digitally competent users who are infrastructure-enabled, showing that when literacy is paired with both self-assurance and environmental support, women are more likely to engage in formal financial systems. This segment exemplifies an ideal outcome of digital finance initiatives, where technical knowledge seamlessly translates into behavior.

In segment 2**,** financial attitude (FA) emerged as the dominant explanatory variable in the DFL–FI pathway. Participants showed moderate levels of digital literacy, but the presence of strong attitudinal orientation compensated for this limitation. Here, DFL influenced FI primarily through FA rather than directly. This suggests that even without advanced technical skills, a favorable disposition toward digital finance can drive meaningful financial inclusion. These findings emphasize the importance of internal belief systems and suggest that psychological readiness can bridge capability gaps.

Segment 3 presented a contrasting scenario: participants exhibited adequate levels of DFL, but poor network infrastructure constrained their ability to convert financial literacy into active financial inclusion. The MNQ variable exerted a strong moderating effect, revealing that external environmental barriers can nullify the benefits of financial literacy and financial confidence. This segment highlights a critical policy concern, namely, the risk of digital financial exclusion despite individual readiness due to infrastructural deficits.

Future research could explore how behavioral segments evolve over time through longitudinal designs, offering insights into the stability or fluidity of inclusion pathways. Applying this segmentation approach to other marginalized groups such as youth, refugees, or disabled populations would also extend its utility and generalizability. Moreover, cross-country comparisons using FIMIX-PLS could reveal structural and cultural differences in digital financial behavior, guiding international policy benchmarking and best practice transfer.

5.2 Recommendations

To respond effectively to these findings, several policy and programmatic recommendations are warranted.

Segment-Specific Program Design: For Segment 1, which comprises digitally competent and infrastructure-enabled women, programs should shift focus from basic financial literacy to innovation and optimization. Financial service providers should develop sophisticated, value-adding tools such as customized micro-insurance, investment platforms, or integrated agri-fintech services. These women are ideal candidates for scaling digital solutions and piloting fintech innovations, as they possess both the readiness and the enabling conditions to maximize impact.

Confidence and Attitudinal Interventions: Segment 2 represents a psychologically motivated group with moderate literacy. Here, interventions should focus on reinforcing self-efficacy and promoting the formation of digital habits. Methods such as peer storytelling, gamification, and trust-building campaigns can help convert positive attitudes into consistent financial behaviours. Digital training should be made contextual and socially relatable, emphasizing relatable role models and community champions who exemplify successful usage.

Infrastructure-First Approach: For Segment 3, infrastructural limitations are the bottleneck. Development efforts should prioritize expanding network reach, improving mobile connectivity, and ensuring reliable electricity. Multistakeholder collaborations between telecom providers, energy co-operatives, and public agencies are necessary to reduce digital deserts. Until infrastructure is stabilized, interventions in this segment should also consider offline or hybrid financial tools to bridge the gap.

Cross-Segment Communication Strategies: Given the varied profiles, a one-size-fits-all communication approach is ineffective. Customized messaging that aligns with each segment's digital maturity and motivational state is essential. For example, Segment 1 may engage better with app-based interfaces, while Segment 2 might respond more to SMS-based nudges or community-led campaigns. Strategic use of digital influencers, radio programs, or WhatsApp forums can reinforce adoption in tailored ways.

Integrated Monitoring and Evaluation: Effective implementation requires systems that can track and evaluate outcomes by behavioral cluster rather than broad demographics. Real-time data dashboards, segment-specific KPIs, and participatory feedback loops will allow program managers to course-correct and refine approaches dynamically. Behavioral segmentation should be embedded within the M&E frameworks of all financial inclusion programs.

Policy Integration: Finally, segmentation insights should inform national financial inclusion policies. Regulatory bodies and ministries should consider behavioral clusters when allocating resources or designing outreach. This would allow for smarter subsidies, targeted incentives, and more equitable financial development. Recognizing that unobserved heterogeneity reflects real socio-behavioral variance, not statistical noise, can elevate the sophistication and impact of inclusive finance strategies.

These findings advance both academic and applied understanding of inclusive finance, demonstrating that segmentation enhances predictive accuracy and the quality of intervention strategies. Future research should explore dynamic segment shifts over time and assess long-term behavioral outcomes from targeted programs.

Author Contributions

Conceptualization: Hamza Malombe ***Methodology:*** Hamza Malombe ***Formal Analysis:*** Hamza Malombe ***Investigation:*** Hamza Malombe ; ***Writing—Original Draft:*** Hamza Malombe ; ***Writing—Review & Editing:*** Hamza Malombe

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Conflicts of Interest: The author declare no conflict of interest.

Data Availability Statement: The data that support the findings of this study are available from the corresponding author, Hamza Malombe, upon reasonable request

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