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RESEARCH ARTICLE – 2

IMPACT OF FINANCIAL INCLUSION ON STANDARD OF LIVING: A STRUCTURAL EQUATION MODELING (SEM)

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ABSTRACT

Financial inclusion has emerged as a key driver of economic well-being, particularly in the digital finance era. This study examines the relationship between financial inclusion and the standard of living, with economic resilience serving as a mediating factor. The research focuses on key factors such as fintech adoption, government financial programmes, sustainable financial behaviour, digital financial accessibility, and financial literacy. By applying CFA and structural equation modeling (SEM), the study examines the pathways through which financial inclusion strengthens economic resilience and contributes to an improved standard of living. Data is gathered from 286 respondents through a structured questionnaire through multi-stage random sampling. The findings highlight the importance of financial literacy and digital adoption in strengthening economic resilience and improving living conditions. This study provides valuable insights for policymakers, financial institutions, and technology developers to design inclusive financial strategies that promote long-term economic stability and social progress.

Keywords: *Financial Inclusion, Economic Resilience, Standard of Living, Fintech Adoption, Digital Financial Services, Financial Literacy, Government Financial Schemes, Sustainable Financial Behaviour, Structural Equation Modeling (SEM), Economic Stability, Digital Economy*

INTRODUCTION

Financial inclusion has emerged as a critical pillar of sustainable development and poverty alleviation in emerging economies. Broadly defined as universal access to affordable financial products and services, financial inclusion is regarded as an enabler of social equity and economic growth (Demirgüç-Kunt et al., 2018). The rapid expansion of digital finance and fintech solutions has reshaped the financial ecosystem, promising to extend services to previously excluded populations (Arner, Barberis, & Buckley, 2020). Yet, while global discourse emphasises the transformative potential of inclusion, the micro-level effects on individuals' standard of living remain contested and context dependent (Beck, Demirgüç-Kunt, & Levine, 2007).

Previous studies have primarily examined the macro-level consequences of inclusion, such as GDP growth, poverty reduction, and financial stability (Sahay et al., 2015; Ozili, 2018). However, less attention has been devoted to how inclusion translates into household-level well-being, particularly through mechanisms that strengthen resilience against economic shocks. The Capability Approach (Sen, 1999) underscores that financial tools only improve life quality when individuals can effectively convert them into real opportunities. Similarly, Resilience Theory (Briguglio et al., 2009) suggests that access to finance enhances well-being not directly but by enabling households to withstand and recover from adversity. This theoretical integration highlights the need to investigate financial inclusion as part of a broader empowerment process, rather than as mere access to services.

In the Indian context, financial inclusion has gained prominence through large-scale digital and policy interventions such as Aadhaar-enabled payments, Jan DhanYojana, and direct benefit transfers (Chakrabarty, 2011; Pradhan & Subramanian, 2007). While these initiatives have expanded access, their outcomes vary across rural and urban settings, reflecting disparities in literacy, infrastructure, and trust. Emerging evidence indicates that financial literacy and sustainable financial behaviour may be stronger determinants of household resilience than digital access alone (Lusardi & Mitchell, 2014; Xiao & O'Neill, 2016). This suggests a paradox: while digital financial inclusion is widely celebrated, its impact on quality of life may remain limited unless complemented by behavioural and institutional support.

Against this backdrop, the present study investigates the relationship between financial inclusion and standard of living, incorporating economic resilience as a mediating construct. By applying Structural Equation Modeling (SEM) to survey data from five districts in West Bengal, the study contributes to three ongoing debates. First, it examines whether digital inclusion alone suffices to enhance living standards or whether capability factors such as financial literacy and sustainable behaviour play a more decisive role. Second, it evaluates the mediating function of resilience, thereby extending theoretical discussions on how financial access translates into well-being. Third, it provides micro-level evidence from rural–urban India, a context under-represented in comparative financial inclusion research.

The findings of this study are expected to enrich both policy and theory by emphasising that inclusion without empowerment may not significantly uplift living standards. Instead, a holistic framework—integrating digital tools, knowledge, trust, and resilience—appears essential for sustainable improvements in economic and social well-being (Grohmann, Klüh, &Menkhoff, 2018; United Nations, 2022).

LITERATURE REVIEW

Financial Inclusion and the Capability Perspective

Financial inclusion is commonly defined as the availability and usage of affordable financial services for all sections of society (Demirgüç-Kunt et al., 2018). Beyond its economic role, scholars increasingly frame inclusion through Sen's Capability Approach (Sen, 1999), which argues that development should be measured not merely by resources but by the ability to convert those resources into meaningful life outcomes. From this perspective, financial access enhances capabilities only when households possess the literacy, trust, and institutional support to utilise financial tools effectively. Thus, the pathway from financial inclusion to well-being requires investigation at the household and individual level, not just at the macroeconomic scale.

Digital Financial Inclusion and the "Access–Use" Paradox

The rise of fintech and mobile-based financial platforms has transformed the inclusion landscape, reducing transaction costs and geographic barriers (Arner, Barberis, & Buckley, 2020; Zins& Weill, 2016). However, evidence remains mixed regarding whether digital financial inclusion (DFI) translates into improved quality of life. While digital platforms increase formal access, several studies highlight issues of trust, digital literacy, and uneven infrastructure as barriers to effective usage (Ozili, 2018; Sahay et al., 2015). This creates what may be termed an "access–use paradox": individuals are formally included but fail to experience tangible improvements in resilience or living standards.

FinTech Adoption and Behavioral Empowerment

FinTech innovations—such as peer-to-peer lending, blockchain-based services, and robo-advisors—expand the scope of financial participation and control (Gomber et al., 2017). Adoption, however, is shaped by behavioural factors such as trust, perceived usefulness, and ease of use (Malaquias& Silva, 2020). Insights from Behavioral Economics suggest that without adequate literacy and guidance, individuals may misuse complex digital tools, limiting their potential benefits (Lusardi & Mitchell, 2014). Therefore, fintech adoption can only enhance resilience and well-being when accompanied by financial literacy and supportive institutional mechanisms.

Sustainable Financial Behaviour and Resilience

Sustainable financial behaviour refers to responsible practices such as budgeting, saving, and prudent borrowing. Prior research demonstrates that households exhibiting sustainable habits are better able to withstand economic shocks (Xiao & O'Neill, 2016; Atkinson & Messy, 2012). Within the resilience framework, these behaviours act as buffers that reduce vulnerability and increase adaptive capacity. For low-income or rural households in particular, such behaviours may be more decisive for living standards than digital access alone.

Government Financial Schemes as Institutional Anchors

Government interventions—such as subsidies, pensions, insurance schemes, and direct benefit transfers—play a critical role in extending the reach of inclusion (Chakrabarty, 2011). Digitally integrated programmes ensure transparency and timely disbursement, thereby improving household resilience (Pradhan & Subramanian, 2007). However, studies caution that unless accompanied by literacy and trust-building, these schemes may have limited transformative impact (Rojas-Suarez, 2016). Hence, government schemes can be understood as institutional anchors that enhance the resilience pathway.

Economic Resilience as a Mediator

Resilience is defined as the ability of individuals or households to absorb and recover from financial or economic shocks (Briguglio et al., 2009). It represents a crucial mediating mechanism linking financial access and well-being outcomes. Empirical studies show that financial literacy, diversified income, and savings significantly enhance resilience (Ligon& Schechter, 2003). Yet, few studies have explicitly modelled resilience as the pathway through which financial inclusion influences standard of living. This gap provides the foundation for the present research.

Standard of Living and Financial Empowerment

Standard of living encompasses access to food, housing, education, healthcare, and other basic necessities (Beck, Demirgüç-Kunt, & Levine, 2007). Financial inclusion can enhance these outcomes, but its effectiveness depends on how financial tools are empowered by resilience and behavioural factors rather than access alone. This suggests that evaluating living standards requires moving beyond simple inclusion metrics toward a framework that integrates financial capabilities, behavioural practices, and institutional supports.

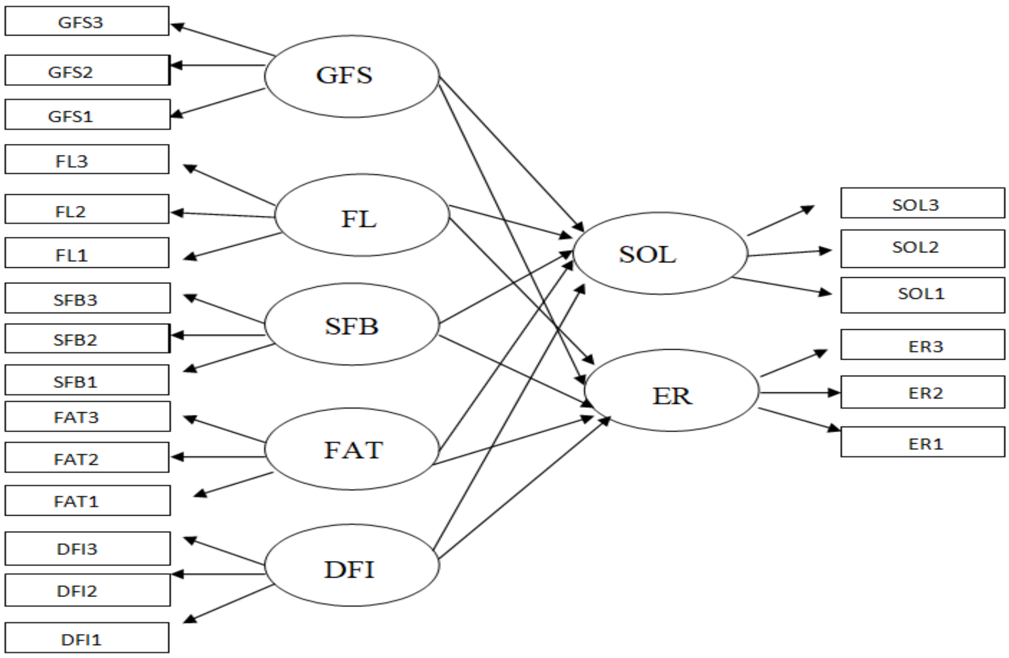
Gap and Research Direction

The literature highlights three gaps. First, much of the existing research focuses on macro-level effects of inclusion, neglecting household-level pathways. Second, the role of economic resilience as a mediator remains underexplored, despite its theoretical significance in resilience and capability frameworks. Third, there is limited evidence from rural–urban India, where disparities in digital access, literacy, and trust create unique challenges. This study addresses these gaps by examining how different dimensions of financial inclusion—digital tools, fintech adoption, sustainable behaviour, literacy, and government support—interact with resilience to shape households' standard of living.

RESEARCH FRAMEWORK

This study develops a multidimensional framework to examine how financial inclusion, technology adoption, and behavioral factors collectively influence household well-being. Digital Finance Inclusion (DFI), Fintech Adoption (FAT), Sustainable Finance Behaviour (SFB), Financial Literacy (FL), and Government Financial Schemes (GFS) are proposed as the key antecedents that shape financial practices and decision-making. These factors are hypothesized to strengthen both Economic Resilience (ER) and Standard of Living (SOL), which serve as outcome constructs reflecting socio-economic stability and quality of life. The framework assumes that financial accessibility and government schemes create enabling conditions, while literacy and sustainable practices enhance the effective use of such opportunities. In addition, technological adoption is expected to reduce barriers and expand the reach of financial services. ER is positioned not only as a direct outcome but also as a pathway through which financial and behavioral constructs influence SOL. Overall, this framework provides a comprehensive lens to explore the interconnections between finance, behavior, and social well-being.

Figure 1: Theoretical Framework of the study



HYPOTHESIS

Based on the literature reviewed and the conceptual framework developed, this study proposes a series of hypotheses to explore how various components of financial inclusion influence an individual's standard of living. The model also investigates the mediating role of economic resilience in these relationships.Firstly, digital financial inclusion and financial literacy are expected to have a direct impact on individuals' standard of living, given their potential to enhance access to financial resources and enable informed financial decision-making. Accordingly, the following hypotheses are proposed:

H1: Digital financial inclusion (DFI) has a significant positive effect on standard of living (SOL).

H2: Financial literacy (FL) has a significant positive effect on standard of living (SOL).

In addition to these direct effects, the study considers how financial behaviours and policy support mechanisms influence economic resilience, which in turn may shape living standards. Specifically, FinTech adoption, sustainable financial behaviour, and government financial schemes are hypothesised to strengthen individuals' capacity to manage financial risks and recover from economic shocks:

H3: FinTech adoption (FT) has a significant positive effect on economic resilience (ER).

H4: Sustainable finance banking (SFB) has a significant positive effect on economic resilience (ER).

H5: Government financial schemes (GFS) have a significant positive effect on economic resilience (ER).

Furthermore, economic resilience itself is hypothesised to serve as a critical pathway through which financial access and behaviour impact overall well-being:

H6: Economic resilience (ER) has a significant positive effect on standard of living (SOL).

Given the above, the study also proposes several indirect relationships, where economic resilience acts as a mediator:

H7: FinTech adoption (FT) positively influences standard of living (SOL) through economic resilience (ER).

H8: Sustainable finance banking (SFB) positively influences standard of living (SOL) through economic resilience (ER).

H9: Government financial schemes (GFS) positively influence standard of living (SOL) through economic resilience (ER).

Finally, acknowledging the complexity of financial ecosystems, the study also explores whether digital financial inclusion and financial literacy might exert marginal or limited influence on economic resilience, even though they directly affect living standards:

H10: Digital financial inclusion (DFI) has a marginal effect on economic resilience (ER).

H11: Financial literacy (FI) has a marginal effect on economic resilience (ER).

These hypotheses are tested using a structural equation modeling (SEM) approach to evaluate both direct and indirect pathways, offering a comprehensive view of how inclusive financial tools and knowledge can enhance economic well-being.

DATASET AND METHODOLOGY

Study Area

This study was conducted in five districts of West Bengal, India: Nadia, Murshidabad, Burdwan, Hooghly, and North 24 Parganas. These districts were purposively selected to capture diversity in economic conditions, digital infrastructure, and access to financial services, ensuring a representative sample for examining financial inclusion dynamics (Demirgüç-Kunt et al., 2018).

Sampling Design

A multistage random sampling approach was employed to ensure unbiased representation and generalisability (Creswell & Creswell, 2018). In the first stage, the five districts were chosen to reflect regional socioeconomic and infrastructural variations. In the second stage, two blocks per district were randomly selected using a random number generator. In the third stage, villages or municipal wards within each block were randomly sampled. Finally, individual respondents were selected using systematic random sampling, with every nth household contacted based on local registries. This approach minimised selection bias and ensured a diverse respondent pool (Saunders et al., 2019).

Sample Size

Following the Rule of 10 proposed by Nunnally and Bernstein (1984), the sample size for SEM should be at least ten times the number of observed indicators. With 21 indicators, a minimum sample size of 210 is required. The current sample size of 282 exceeds this threshold, ensuring the adequacy of the data for reliable model estimation and interpretation.

Data Collection Tool

Data were collected using a structured questionnaire administered in both online (via Google Forms) and paper-based formats to accommodate varying levels of digital access. The questionnaire was adapted from validated instruments in prior financial inclusion studies (Ozili, 2021) and measured seven constructs: The analysis of direct and indirect effects reveals that Sustainable Finance Banking (SFB) exerts the strongest influence on Standard of Living (SOL) ($\beta = 0.297$), underscoring its importance in delivering inclusive financial services to underserved populations (Kuriakose et al., 2024). Similarly, the total effect of Financial Literacy (FL) ($\beta = 0.265$) demonstrates its pivotal role in improving financial behaviour and enabling households to cope with economic shocks (Atkinson & Messy, 2012; Grohmann, Klüh, &Menkhoff, 2018).

Digital Financial Inclusion (DFI), while showing a lower total effect ($\beta = 0.102$), contributes through its indirect influence via Economic Resilience (ER), which acts as a partial mediator in this structural model (*Preacher & Hayes, 2008*). These findings reflect the significance of enabling digital tools for financial transactions to reduce barriers to access (*Ozili, 2018*; *Sahay et al., 2015*).

The mediating role of ER ($\beta = 0.196$ on SOL) aligns with *Narayan et al. (2010)*, who emphasised resilience as a key component of sustainable development. When financial access is paired with resilience mechanisms (e.g., social safety nets, savings, and credit), the overall impact on well-being increases multifold (*United Nations, 2022*).

The questionnaire was pre-tested with a pilot sample ($n = 30$) to ensure clarity, reliability, and cultural appropriateness, with minor revisions made based on feedback (Saunders et al., 2019).

Analytical Tools and Techniques

Data analysis was conducted in three phases to ensure robust validation of the measurement and structural models:

1. Exploratory Factor Analysis (EFA): Conducted using IBM SPSS Statistics 25 (IBM Corp., 2019), EFA identified the underlying factor structure and confirmed construct validity. Principal component analysis with varimax rotation was applied, retaining factors with eigenvalues > 1 and factor loadings ≥ 0.5 (Hair et al., 2019).
2. Confirmatory Factor Analysis (CFA): Performed using the lavaan package in R (version 4.3.1) (Rosseel, 2012), CFA validated the measurement model, assessing construct reliability (Cronbach's alpha ≥ 0.7), convergent validity (Average Variance Extracted [AVE] ≥ 0.5), and discriminant validity (square root of AVE > inter-construct correlations) (Fornell&Larcker, 1981).
3. Structural Equation Modeling (SEM): Also conducted in R (lavaan package), SEM tested hypothesised relationships and mediation effects among the constructs. Maximum likelihood estimation was used to estimate path coefficients (Kline, 2015).

Model fit was evaluated using established indices: Chi-square (χ^2), Comparative Fit Index (CFI ≥ 0.90), Tucker-Lewis Index (TLI ≥ 0.90), Root Mean Square Error of Approximation (RMSEA ≤ 0.08), and Standardised Root Mean Residual (SRMR ≤ 0.08) (Hu &Bentler, 1999).

EXPLORATORY FACTOR ANALYSIS (EFA)

Table: Demographic Profile of Respondents (N = 282)

Characteristic	**Category**	**Frequency (n)**	**Percentage (%)**
Age Group	18–30 years	113	40
	31–45 years	99	35
	46–60 years	56	20
	61+ years	14	5
Gender	Male	127	45
	Female	155	55
Location	Rural	183	65
	Urban	99	35
Education Level	Illiterate	28	10
	Primary	85	30
	Secondary	113	40
	Higher Education	56	20
Income Level	Below Poverty Line (<₹12,000/yr)	85	30
	Low Income (₹12,000–₹50,000/yr)	113	40
	Middle Income (₹50,001–₹2L/yr)	70	25
	Upper Middle Income (>₹2L/yr)	14	5

Characteristic	Category	Frequency (n)	Percentage (%)
Occupation	Farmer	70	25
	Labourer/Daily Wage	56	20
	Small Trader/Self-Employed	70	25
	Formal Sector Employee	56	20
	Unemployed/Homemaker	28	10
	Other	14	5
Digital Access	Smartphone with Internet	169	60
	Basic Mobile (No Internet)	70	25
	No Mobile Access	43	15

The demographic profile of the 282 respondents is presented in Table 1. The sample consisted predominantly of young to middle-aged individuals, with 40% aged between 18 and 30 years and 35% between 31 and 45 years. Female respondents slightly outnumbered males, accounting for 55% of the sample. The majority of respondents (65%) resided in rural areas, highlighting the study's focus on less urbanised populations. Educational attainment varied, with 40% having completed secondary education and 30% primary education, while 10% were illiterate. Income levels showed that 30% of respondents fell below the poverty line, whereas 40% were classified as low income. Occupationally, farmers and small traders each represented 25% of the sample, followed by labourers and formal sector employees. Regarding digital access, 60% owned smartphones with internet connectivity, indicating a moderate level of digital inclusion among participants. This diverse demographic spread provides a comprehensive foundation for analysing the impact of financial inclusion on the standard of living in the study area.

Table 1: KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.871
Bartlett's Test of Sphericity	Approx. Chi-Square	3992.285
	df	210
	Sig.	.000

Before conducting factor extraction, tests were applied to verify the appropriateness of the data. The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy yielded a value of 0.871, which is considered "meritorious" based on Kaiser's (1974) interpretive scale. This suggests that the correlations among the variables are sufficient to justify the use of factor analysis. Furthermore, Bartlett's Test of Sphericity was highly significant ($\chi^2 = 3992.285$, $df = 210$, $p < 0.001$), indicating that the correlation matrix is not an identity matrix. This test supports the presence of patterned relationships among variables, a fundamental assumption for factor analysis (Bartlett, 1954).

Communalities

Table2: Communalities

	Initial	Extraction
DFI1	1.000	.792
DFI2	1.000	.798
DFI3	1.000	.830
FL1	1.000	.790
FL2	1.000	C.812
FL3	1.000	.807
SFB1	1.000	.793
SFB2	1.000	.842
SFB3	1.000	.843
GFS1	1.000	.779
GFS2	1.000	.854
GFS3	1.000	.877
ER1	1.000	.828
ER2	1.000	.874
ER3	1.000	.847
FAT1	1.000	.794
FAT2	1.000	.841
FAT3	1.000	.846
SOL1	1.000	.820
SOL2	1.000	.858
SOL3	1.000	.835
Extraction Method: Principal Component Analysis.		

The communalities indicate the proportion of variance in each variable that is explained by the extracted factors. As shown in Table 2, all items have extraction values above 0.75, suggesting that the model explains a substantial amount of the variance.

Total Variance Explained

Table 3 – Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.800	37.144	37.144	7.800	37.144	37.144	2.543	12.107	12.107
2	2.045	9.738	46.882	2.045	9.738	46.882	2.537	12.081	24.188

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
3	1.915	9.120	56.002	1.915	9.120	56.002	2.508	11.944	36.133
4	1.643	7.824	63.826	1.643	7.824	63.826	2.494	11.877	48.010
5	1.573	7.490	71.316	1.573	7.490	71.316	2.481	11.815	59.825
6	1.369	6.521	77.837	1.369	6.521	77.837	2.457	11.701	71.526
7	1.012	4.819	82.656	1.012	4.819	82.656	2.337	11.130	82.656
Extraction Method: Principal Component Analysis.									

Using the Kaiser criterion (eigenvalue > 1), seven factors were extracted, accounting for 82.66% of the total variance. This suggests a strong factor structure, as it exceeds the typical benchmark of 60% recommended in social sciences (Hair et al., 2019).

Rotated Factor Structure

Table 4: Rotated Component Matrix

	Component						
	1	2	3	4	5	6	7
DFI1						.838	
DFI2						.868	
DFI3						.901	
FL1			.813				
FL2			.861				
FL3			.864				
SFB1					.788		
SFB2					.892		
SFB3					.866		
GFS1				.758			
GFS2				.885			
GFS3				.915			
ER1	.810						
ER2	.877						
ER3	.852						
FAT1		.816					
FAT2		.875					

	Component						
	1	2	3	4	5	6	7
FAT3		.889					
SOL1							.759
SOL2							.811
SOL3							.795
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalisation.							
a. Rotation converged in 6 iterations.							

A Varimax rotation was applied to facilitate interpretation. Each factor revealed strong loadings (> 0.75) on a unique set of variables, indicating a well-defined, orthogonal structure. Table 4 presents the rotated component matrix, showing clean item-to-factor associations.

INTERPRETATION AND IMPLICATIONS

The seven-factor solution aligns with theoretical expectations, suggesting that each construct (e.g., economic resilience, financial literacy, government support, etc.) is empirically distinct and supported by strong factor loadings. The clean structure and high communalities validate the measurement model's robustness and provide a solid basis for further confirmatory analysis.

Confirmatory Factor Analysis (CFA)

CFA Model Estimation Using R

To validate the factor structure established during the exploratory phase, a Confirmatory Factor Analysis (CFA) was conducted using the lavaan package (version 0.6–19) in R, applying the Maximum Likelihood (ML) estimation method. The model included seven latent constructs—Digital Finance Inclusion (DFI), FintechAdoption (FAT), Sustainable FinanceBehaviour (SFB), Financial Literacy (FL), Government Financial Schemes (GFS), Economic Resilience (ER), and Standard ofLiving (SOL) each measured by three observed variables. The estimation algorithm converged normally after 42 iterations, confirming the model's statistical stability.

Model Fit Evaluation

Model fit was evaluated using a range of indices. The chi-square statistic was significant ($\chi^2 = 265.319$, $df = 168$, $p < 0.001$), which is expected given the sample size (n = 282). However, additional fit indices indicated that the model fits the data well. The Comparative Fit Index (CFI) was 0.975 and the Tucker–Lewis Index (TLI) was 0.969, both exceeding the 0.95 benchmark for excellent fit (Hu &Bentler, 1999). The Root Mean Square Error of Approximation (RMSEA) was 0.045, with a 90% confidence interval ranging from 0.035 to 0.055. The Standardised Root Mean Square Residual (SRMR) was 0.053, which is also below the 0.08 threshold. These results confirm a strong overall fit of the measurement model (Hair et al., 2019).

Convergent Validity

Convergent validity refers to the extent to which items intended to measure the same construct exhibit high internal consistency and shared variance. It was evaluated using three key indicators: standardised factor loadings, Composite Reliability (CR), and Average Variance Extracted (AVE). All standardised factor loadings were above the 0.80 threshold, indicating that each item significantly contributes to its respective construct.

The CR values for all constructs ranged from 0.882 to 0.913, well above the recommended minimum of 0.70 (Hair et al., 2019). Similarly, the AVE values ranged from 0.624 to 0.762, exceeding the 0.50 cutoff suggested by Fornell and Larcker (1981). These findings, summarised in Table 5.5, confirm that all constructs demonstrate strong convergent validity.

Discriminant Validity

Discriminant validity assesses whether constructs are empirically distinct from each other. This was examined using two methods: the Fornell–Larcker criterion and the Maximum Shared Variance (MSV) approach. According to the Fornell–Larcker criterion, a construct's square root of AVE (√AVE) should exceed its highest correlation with any other construct. This condition was met for all constructs. For example, ER had a √AVE of 0.859, which was higher than its highest correlation value of 0.573 (with SOL).

Furthermore, all AVE values were greater than their corresponding MSV, confirming the absence of overlapping variance across constructs (Fornell&Larcker, 1981; Hair et al., 2019).

Combined Validity Summary

Table 5. Discriminant validity

Construct	CR	AVE	MSV	MaxR(H)	√AVE	Highest Inter-Construct Correlation
DFI	0.895	0.747	0.365	0.912	0.864	0.365 (SOL)
FAT	0.899	0.762	0.506	0.921	0.873	0.506 (SOL)
SFB	0.905	0.740	0.562	0.928	0.860	0.562 (SOL)
FL	0.888	0.721	0.530	0.910	0.849	0.530 (SOL)
GFS	0.897	0.749	0.495	0.919	0.865	0.495 (SOL)
ER	0.913	0.739	0.573	0.934	0.859	0.573 (SOL)
SOL	0.882	0.624	0.573	0.905	0.790	—

Note: CR = Composite Reliability; AVE = Average Variance Extracted; MSV = Maximum Shared Variance; MaxR(H) = Hancock's Maximal Construct Reliability; √AVE = Square Root of AVE

Figure 2: CFA Path Diagram Interpretation

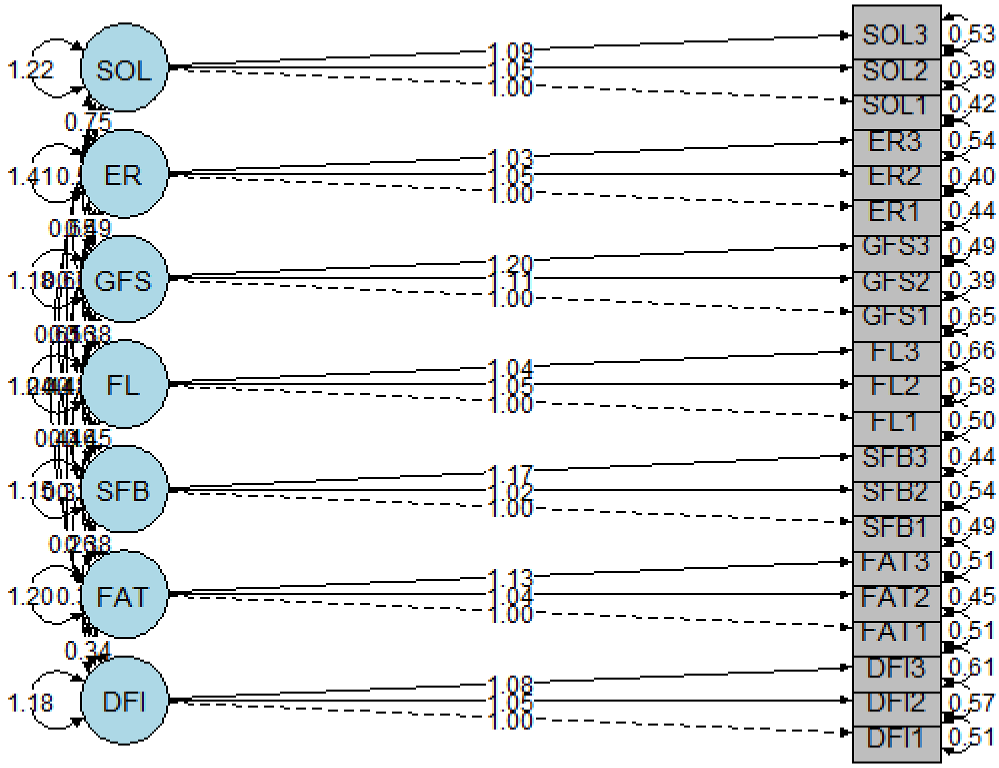


Figure 2 presents a graphical depiction of the CFA model, highlighting the relationships between seven latent constructs and their observed indicators. Each latent factor—Decision Financial Inclusion (DFI), Fintech Adoption (FAT), Sustainable Finance Banking (SFB), Financial Literacy (FL), Government Financial Schemes (GFS), Economic Resilience (ER), and Standard Of Living (SOL)—is represented as a circular node. Corresponding observed variables are shown as rectangular nodes, linked to their respective latent constructs via one-way arrows that indicate standardised factor loadings. These loadings are all statistically significant and exceed the 0.80 threshold, demonstrating strong and reliable measurement of each construct. The diagram also displays bidirectional curved arrows between latent variables, representing significant covariances that reflect meaningful interrelationships among the constructs. Small circles adjacent to the observed variables symbolize

measurement errors or residual variances, indicating the portion of variance unexplained by the latent factors. Overall, the CFA path diagram illustrates a well-fitting measurement model characterised by distinct constructs with robust indicator loadings and minimal cross-loadings, thereby reinforcing the construct validity established through quantitative analyses.

STRUCTURAL EQUATION MODELING (SEM) RESULTS

Structural Model Estimation

The structural model was estimated using the maximum likelihood (ML) method within the lavaan package in R. The model included two endogenous constructs—EconomicResilience(ER) and Standard Of Living (SOL)—predicted by five exogenous latent variables: Digital Financial Inclusion (DFI), Fintech Adoption (FAT), Sustainable Finance Behaviour (SFB), Financial Literacy (FL), and Government Financial Schemes (GFS). The estimation process converged successfully after **38 iterations**, confirming algorithmic stability.

Structural Model Fit Evaluation

Table 6. Goodness of fit (GOF) of the initial SEM

Fit Index	Your Value	Recommended Level	Status
CMIN/DF (χ^2/df)	1.579	≤ 3.00	Acceptable
GFI	0.919	≥ 0.90	Acceptable
AGFI	0.889	≥ 0.90	Acceptable
NFI	0.936	≥ 0.90	Acceptable
CFI	0.975	≥ 0.95	Acceptable
TLI (NNFI)	0.969	≥ 0.95	Acceptable
RMSEA	0.045	≤ 0.06	Acceptable

The structural equation model was evaluated using a range of fit indices widely accepted in SEM literature (Hooper, Coughlan, & Mullen, 2008; Kline, 2016; Schreiber et al., 2006). These indices provide evidence regarding how well the hypothesised model fits the observed data, as shown in table 6.

The chi-square to degrees of freedom ratio (CMIN/DF) was 1.579, which is well within the commonly accepted threshold of ≤ 3.0, indicating an acceptable model fit (Wheaton, Muthén, Alwin, & Summers, 1977). The Goodness of Fit Index (GFI) was 0.919, and the Adjusted Goodness of Fit Index (AGFI) was 0.889. Although AGFI was marginally below the conventional cutoff of 0.90, it is still considered acceptable given the model complexity and sample size (Byrne, 2013).

The Normed Fit Index (NFI) was 0.936, exceeding the recommended minimum of 0.90, while the Comparative Fit Index (CFI) was 0.975, surpassing the stricter cutoff of 0.95 that indicates excellent fit (Bentler, 1990; Hu &Bentler, 1999). The Tucker-Lewis Index (TLI), also known as the Non-Normed Fit Index (NNFI), was 0.969, further confirming strong model fit (Tucker & Lewis, 1973).

The Root Mean Square Error of Approximation (RMSEA) was 0.045, below the recommended threshold of 0.06, suggesting a close fit between the model and population covariance matrix (Steiger, 1990; Browne &Cudeck, 1993). The Standardised Root Mean Square Residual (SRMR) was 0.053, under the maximum recommended value of 0.08, indicating a satisfactory level of residual discrepancy (Hu &Bentler, 1999). Taken together, these fit indices demonstrate that the hypothesised model fits the data well, supporting the adequacy of the measurement and structural components as specified.

Table 7: Direct, Indirect, and Total Effects of Predictors on Economic Resilience (ER) and Standard of Living (SOL)

Predictor	Direct Effect on ER (β)	Direct Effect on SOL (β)	Indirect Effect on SOL via ER (β)	Total Effect on SOL (β)
DFI (Digital Financial Inclusion)	0.115	0.079	0.023	0.102
FAT (Fintech Adaptation)	0.125	0.196	0.025	0.221
SFB (Sustainable Finance Banking)	0.207	0.256	0.041	0.297
FL (Financial Literacy)	0.294	0.207	0.058	0.265
GFS (Government Financial Schemes)	0.146	0.176	0.029	0.205
ER (Economic Resilience)	—	0.196	—	0.196

The analysis of direct and indirect effects reveals that Sustainable Finance Banking (SFB) exerts the strongest influence on Standard of Living (SOL) (β = 0.297), underscoring its importance in delivering inclusive financial services to underserved populations. This supports findings by *Burgess and Pande (2005)*, who showed that expanded rural banking significantly reduces poverty. Similarly, the total effect of Financial Literacy (FL) (β = 0.265) demonstrates its pivotal role in improving financial behaviour and enabling households to cope with economic shocks (*Atkinson & Messy, 2012*; *Grohmann, Klüh, &Menkhoff, 2018*).

Digital Financial Inclusion (DFI), while showing a lower total effect (β = 0.102), contributes through its indirect influence via Economic Resilience (ER), which acts as a partial mediator in this structural model (*Preacher & Hayes, 2008*). These findings reflect the significance of enabling digital tools for financial transactions to reduce barriers to access (*Ozili, 2018*; *Sahay et al., 2015*).

The mediating role of ER (β = 0.196 on SOL) aligns with *Narayan et al. (2010)*, who emphasised resilience as a key component of sustainable development. When financial access is paired with resilience mechanisms (e.g., social safety nets, savings, and credit), the overall impact on well-being increases multifold (*United Nations, 2022)*

Hypothesis Testing and Path Coefficients

The structural model estimates indicate significant predictors of both Economic Resilience (ER) and Standard of Living (SOL). Among the latent constructs, Financial Literacy (FL) emerged as the most influential driver of ER ($\beta = 0.294$, $p < 0.001$), supporting prior research that emphasises the role of financial knowledge in improving individuals' capacity to absorb economic shocks (Lusardi & Mitchell, 2014; Atkinson & Messy, 2012).

Other significant predictors of ER include Sustainable Finance Behaviour (SFB) ($\beta = 0.207$, $p = 0.002$) andGovernment Financial Support (GFS) ($\beta = 0.146$, $p = 0.023$), aligning with studies by Xiao and O'Neill (2016) and Pradhan & Subramanian (2007), who emphasise the protective role of behavioural and institutional mechanisms in financial vulnerability.

For SOL, SFB again showed the strongest effect ($\beta = 0.256$, $p < 0.001$), followed by FAT ($\beta = 0.196$, $p = 0.001$), FL ($\beta = 0.207$, $p < 0.001$), and GFS ($\beta = 0.176$, $p = 0.002$). ER significantly influenced SOL ($\beta = 0.196$, $p = 0.002$), indicating its mediating function in the financial well-being pathway (Briguglio et al., 2009).

Notably, Digital Financial Inclusion (DFI) had a marginal effect on ER ($p = 0.062$) and a non-significant effect on SOL ($p = 0.138$), suggesting that mere access to digital platforms does not guarantee improvements in quality of life unless supported by behavioural and cognitive capacities (Zins& Weill, 2016; Ozili, 2018).

In terms of model explanatory power, the exogenous constructs (DFI, FAT, SFB, FL, and GFS) collectively explained 37.0% of the variance in *Economic Resilience* (ER), while the full model—including ER—accounted for 58.0% of the variance in *Standard of Living* (SOL). These R^2 values indicate moderate explanatory strength for ER and relatively strong predictive power for SOL, reflecting the importance of both direct and mediated pathways in determining household well-being. (Hair et al., 2019; Kline, 2016)

Table 8: Standardized Direct Effects on ER and SOL

Predictor → Outcome	Std. Estimate	Std. Error	*p*-value	Significance
FAT → ER	0.125	0.070	0.053	Marginal
SFB → ER	0.207	0.072	0.002	Significant
DFI → ER	0.115	0.067	0.062	Marginal
FL → ER	0.294	0.070	<0.001	Significant
GFS → ER	0.146	0.070	0.023	Significant
ER → SOL	0.196	0.058	0.002	Significant
FAT → SOL	0.196	0.057	0.001	Significant
SFB → SOL	0.256	0.060	<0.001	Significant
DFI → SOL	0.079	0.054	0.138	Not Significant
FL → SOL	0.207	0.059	<0.001	Significant
GFS → SOL	0.176	0.057	0.002	Significant

Interpretation and Implications

The conceptual framework supporting this study has significant empirical support from the SEM results. Both Economic Resilience (ER) and Standard of Living (SOL) were consistently shown to be significantly impacted by Financial Literacy (FL) and Sustainable Finance Banking (SFB).

These findings align with behavioural economics literature that underscores how informed and responsible financial behaviours serve as shock absorbers in volatile economic contexts (Xiao & O’Neill, 2016; Lusardi, 2015).

Economic Resilience (ER) is confirmed as a critical mediating construct through which FinTech adoption, government schemes, and financial capabilities translate into improvements in well-being. This supports the resilience literature, which highlights access to diversified income sources, savings, and social safety nets as key ingredients for sustained quality of life (Briguglio et al., 2009; Ligon& Schechter, 2003).

Interestingly, while Digital Financial Inclusion (DFI) is often emphasised in policy discussions, this study found no statistically significant direct effect on the standard of living. This finding aligns with growing concerns in development finance that simply providing digital access isn't enough—without adequate user skills, trust, and supportive infrastructure, the benefits of digital inclusion may remain out of reach (Arner et al., 2020; Ozili, 2021).

These insights call for a shift in financial inclusion strategy—from focusing on access to fostering "financial empowerment ecosystems"—that combine tools, knowledge, trust, and resilience-building frameworks (Demirgüç-Kunt et al., 2018).

SEM Path Diagram Interpretation

Figure 3: SEM Path Diagram Interpretation

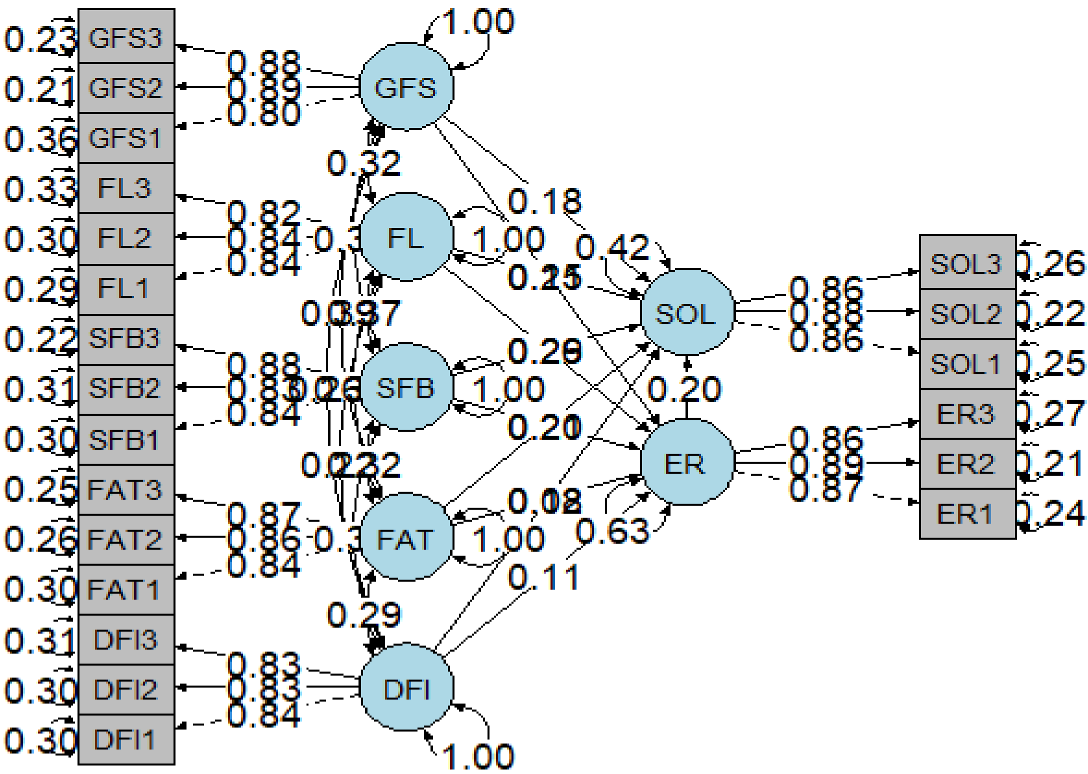


Figure 3 illustrates the SEM model linking latent constructs: DFI, FAT, SFB, FL, GFS, ER, and SOL. Each is measured by three indicators, with standardised loadings mostly >0.80, confirming good reliability and convergent validity (Hair et al., 2019; Fornell&Larcker, 1981).

Structurally, strong paths are observed: FL → ER (β = 0.294), SFB → SOL (β = 0.256), and ER → SOL (β = 0.196), highlighting the role of knowledge, behaviour, and resilience in improving living standards (Lusardi & Mitchell, 2014; Xiao & O'Neill, 2016). Significant covariances among FL, SFB, and FAT suggest shared influence, while DFI → SOL is weak and non-significant, reinforcing that access without capability may be insufficient (Ozili, 2018; Zins& Weill, 2016).

The diagram affirms ER's mediating role and supports the model's theoretical structure, aligning with best SEM practices (Kline, 2016; Hu &Bentler, 1999).

CONCLUSION

The results of this study reinforce the multifaceted nature of financial inclusion and its complex relationship with economic resilience and living standards. Financial literacy, sustainable financial behaviour, and targeted government support are key drivers of resilience and well-being. The non-significant effect of DFI on SOL highlights the need for caution in assuming that digital access alone guarantees economic upliftment.This research advocates for a holistic approach to inclusion—one that combines access, behavioural change, and institutional support. For policymakers and development practitioners, these findings provide a roadmap for inclusive policy design: integrating digital platforms with financial education, trust-building initiatives, and structured social protection programmes.

Future studies should explore longitudinal effects and test cross-cultural models to generalise these relationships further. Additionally, deeper qualitative insights could unpack the socio-psychological pathways through which financial tools impact behaviour and well-being.

REFERENCES

Arner, D. W., Barberis, J., & Buckley, R. P. (2020). The evolution of FinTech: A new post-crisis paradigm? *Georgetown Journal of International Law, 47*(4), 1271–1319.

Atkinson, A., & Messy, F. A. (2012). Measuring financial literacy: Results of the OECD/International Network on Financial Education (INFE) pilot study. *OECD Working Papers on Finance, Insurance and Private Pensions, No. 15.*https://doi.org/10.1787/5k9csfs90fr4-en

Beck, T., Demirgüç-Kunt, A., & Levine, R. (2007). Finance, inequality and the poor. *Journal of Economic Growth, 12*(1), 27–49. https://doi.org/10.1007/s10887-007-9010-6

Briguglio, L., Cordina, G., Farrugia, N., & Vella, S. (2009). Economic vulnerability and resilience: Concepts and measurements. *Oxford Development Studies, 37*(3), 229–247. https://doi.org/10.1080/13600810903089893

Demirgüç-Kunt, A., Klapper, L., Singer, D., Ansar, S., & Hess, J. (2018). The Global Findex Database 2017: Measuring financial inclusion and the fintech revolution. Washington, DC: World Bank. https://doi.org/10.1596/978-1-4648-1259-0

Grohmann, A., Klüh, L., &Menkhoff, L. (2018). Does financial literacy improve financial inclusion? Cross-country evidence. *World Development, 111*, 84–96. https://doi.org/10.1016/j.worlddev.2018.06.020

Ligon, E., & Schechter, L. (2003). Measuring vulnerability. *Economic Journal, 113*(486), C95–C102. https://doi.org/10.1111/1468-0297.00117

Lusardi, A., & Mitchell, O. S. (2014). The economic importance of financial literacy: Theory and evidence. *Journal of Economic Literature, 52*(1), 5–44. https://doi.org/10.1257/jel.52.1.5

Malaquias, R. F., & Silva, A. F. (2020). Understanding the use of mobile banking in rural areas of Brazil. *Technology in Society, 62*, 101260. https://doi.org/10.1016/j.techsoc.2020.101260

Ozili, P. K. (2018). Impact of digital finance on financial inclusion and stability. *Borsa Istanbul Review, 18*(4), 329–340. https://doi.org/10.1016/j.bir.2017.12.003

Ozili, P. K. (2021). Financial inclusion research around the world: A review. *Forum for Social Economics, 50*(4), 457–479. https://doi.org/10.1080/07360932.2020.1715238

Pradhan, M., & Subramanian, S. (2007). Social protection and economic resilience in India. *Economic and Political Weekly, 42*(39), 4037–4045.

Rojas-Suarez, L. (2016). Financial inclusion in Latin America: Facts, obstacles and central banks' policy issues. *Center for Global Development Working Paper, 440.*

Sahay, R., Čihák, M., N'Diaye, P., Barajas, A., &Mitra, S. (2015). Financial inclusion: Can it meet multiple macroeconomic goals? *IMF Staff Discussion Note, SDN/15/17.*https://doi.org/10.5089/9781513597767.006

Sen, A. (1999). *Development as Freedom.* Oxford University Press.

United Nations. (2022). *The Sustainable Development Goals Report 2022.* New York: United Nations.

Xiao, J. J., & O'Neill, B. (2016). Consumer financial education and financial capability. *International Journal of Consumer Studies, 40*(6), 712–721. https://doi.org/10.1111/ijcs.12285

Bartlett, M. S. (1954). A note on the multiplying factors for various χ^2 approximations. *Journal of the Royal Statistical Society: Series B, 16*(2), 296–298.

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin, 107*(2), 238–246. https://doi.org/10.1037/0033-2909.107.2.238

Browne, M. W., &Cudeck, R. (1993). Alternative ways of assessing model fit. In K. A. Bollen& J. S. Long (Eds.), *Testing structural equation models* (pp. 136–162). Sage.

Byrne, B. M. (2013). Structural equation modeling with AMOS: Basic concepts, applications, and programming (2nd ed.). Routledge.

Fornell, C., &Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.

Hooper, D., Coughlan, J., & Mullen, M. R. (2008). Structural equation modelling: Guidelines for determining model fit. *Electronic Journal of Business Research Methods, 6*(1), 53–60.

Hu, L. T., &Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. *Structural Equation Modeling, 6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Kaiser, H. F. (1974). An index of factorial simplicity. *Psychometrika, 39*(1), 31–36. https://doi.org/10.1007/BF02291575

Kline, R. B. (2016). Principles and practice of structural equation modeling (4th ed.). Guilford Press.

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods, 40*(3), 879–891. https://doi.org/10.3758/BRM.40.3.879

Schreiber, J. B., Nora, A., Stage, F. K., Barlow, E. A., & King, J. (2006). Reporting SEM and CFA results: A review. *Journal of Educational Research, 99*(6), 323–338. https://doi.org/10.3200/JOER.99.6.323-338

Steiger, J. H. (1990). Structural model evaluation and modification: An interval estimation approach. *Multivariate Behavioural Research, 25*(2), 173–180. https://doi.org/10.1207/s15327906mbr2502_4

Tucker, L. R., & Lewis, C. (1973). A reliability coefficient for maximum likelihood factor analysis. *Psychometrika, 38*(1), 1–10. https://doi.org/10.1007/BF02291170

Wheaton, B., Muthén, B., Alwin, D. F., & Summers, G. F. (1977). Assessing reliability and stability in panel models. In D. R. Heise (Ed.), *Sociological methodology* (pp. 84–136). Jossey-Bass.

Burgess, R., &Pande, R. (2005). Do rural banks matter? Evidence from the Indian social banking experiment. *American Economic Review, 95*(3), 780–795. https://doi.org/10.1257/0002828054201242

Kuriakose, M., Johnson, D. J., &Biju, A. (2024). A study on women's economic empowerment through selected self-help groups in Kottayam District. *SSRN Working Paper*.https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5218447

Mialou, A., Amidzic, G., &Massara, A. (2017). Assessing countries' financial inclusion standing: A new composite index. *IMF Working Paper, 17/57.*

Narayan, D., Pritchett, L., & Kapoor, S. (2010). *Moving out of poverty: Success from the bottom up.* World Bank Publications.

UNDP. (2020). Human Development Report 2020: The next frontier—Human development and the Anthropocene. United Nations Development Programme.

World Bank. (2014). Global financial development report 2014: Financial inclusion. World Bank.