Structural Equation Modelling of User Trust, AI-Driven FinTech Services, and Financial Inclusion in the Digital Economy

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ABSTRACT

The rapid diffusion of Artificial Intelligence (AI) in Financial Technology (FinTech) has redefined the mechanisms through which financial services are delivered and accessed in the digital economy. While AI-driven FinTech services are widely promoted as enablers of financial inclusion, empirical evidence explaining how these technologies translate into inclusive outcomes remains limited, particularly with respect to the role of user trust. This study investigates the structural relationships among AI-driven FinTech services, user trust, and financial inclusion using a Structural Equation Modelling (SEM) approach. Based on survey data collected from active users of AI-enabled FinTech platforms, the measurement model demonstrates strong reliability and convergent validity, with all constructs achieving Composite Reliability values above 0.85 and Average Variance Extracted values exceeding 0.60. Structural analysis reveals that AI-driven FinTech services have a significant positive effect on user trust ($\beta = 0.62$, $p < 0.001$) and a direct positive effect on financial inclusion ($\beta = 0.18$, $p < 0.05$). User trust, in turn, exerts a substantial influence on financial inclusion ($\beta = 0.55$, $p < 0.001$), confirming its critical role in shaping inclusive financial engagement. Mediation analysis further indicates that user trust partially mediates the relationship between AI-driven FinTech services and financial inclusion, with the indirect effect ($\beta = 0.34$) exceeding the magnitude of the direct effect. These findings demonstrate that the inclusionary impact of AI-driven FinTech services is predominantly transmitted through trust formation rather than technological capability alone. The study contributes to FinTech and digital inclusion literature by empirically establishing a trust-centered causal pathway and highlights the importance of transparent, reliable, and user-oriented AI governance for achieving sustainable financial inclusion in the digital economy.

Keywords Artificial Intelligence, Financial Technology, User Trust, Financial Inclusion, Structural Equation Modelling, Digital Economy

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INTRODUCTION

The rapid expansion of FinTech has fundamentally transformed the structure of financial service delivery in the digital economy. Through the integration of AI, FinTech platforms increasingly rely on automated credit scoring, personalized financial recommendations, algorithmic risk assessment, and intelligent payment systems to improve efficiency and scalability [1], [2]. While these innovations promise broader access to financial services, empirical evidence shows that technological sophistication alone does not automatically translate into financial inclusion, particularly for underserved and vulnerable populations [3], [4].

A critical challenge underlying AI-driven FinTech adoption is the issue of user trust. AI systems often operate as opaque decision-making mechanisms,

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raising concerns regarding explainability, fairness, data privacy, and accountability [5], [6]. In financial contexts, where decisions directly affect individuals' economic opportunities, trust becomes a prerequisite for sustained usage and engagement [7]. Studies have shown that perceived algorithmic bias, lack of transparency, and uncertainty about data governance can undermine trust and limit the inclusionary potential of digital financial services [8], [9].

Despite the growing body of research on FinTech adoption and AI applications, the mechanisms linking AI-driven services to financial inclusion remain insufficiently understood. Prior studies frequently examine technology acceptance, performance efficiency, or innovation diffusion in isolation, without explicitly modeling the mediating psychological processes that convert technological capability into inclusive outcomes [10], [11]. In particular, empirical investigations that simultaneously analyze AI capability, user trust, and financial inclusion within a unified causal framework remain scarce [12].

Another limitation in the existing literature lies in methodological fragmentation. Many studies rely on regression-based approaches or descriptive analyses that are unable to capture the complex, multi-dimensional relationships among latent constructs such as trust and inclusion [13]. This restricts the ability to test indirect effects and obscures the role of trust as a structural transmission channel. Consequently, there is a need for robust analytical methods capable of modeling simultaneous relationships and mediation effects within AI-enabled financial ecosystems [14].

To address these gaps, this study employs SEM to investigate the relationships among AI-driven FinTech services, user trust, and financial inclusion in the digital economy. SEM enables the simultaneous estimation of measurement and structural models, allowing for rigorous validation of latent constructs and the testing of both direct and indirect effects [15], [16]. By positioning user trust as a mediating variable, the study explicitly examines how AI-enabled functionalities translate into inclusion outcomes through psychological acceptance and confidence formation.

The novelty of this research lies in its integrated trust-centered SEM framework for AI-driven financial inclusion. Unlike prior studies that treat trust as a peripheral factor or control variable, this study conceptualizes trust as a core structural mechanism linking AI innovation to inclusive financial participation [17], [18]. This approach advances theoretical understanding by reframing financial inclusion as a socio-technical outcome shaped by both algorithmic performance and user perception.

Ultimately, this study contributes to FinTech scholarship and practice by providing empirical evidence that inclusive digital finance requires more than advanced algorithms. It requires trust-aware AI design, transparent governance, and user-centric system architectures that align technological innovation with social legitimacy. These insights are intended to inform FinTech developers, policymakers, and regulators seeking to harness AI responsibly while promoting equitable access to financial services in the digital economy [19], [20].

Literature Review

The evolution of FinTech in the digital economy has been widely discussed as a structural transformation of financial intermediation, driven by the convergence of digital platforms, data analytics, and AI. Prior studies emphasize that AI enhances financial services through automation, predictive analytics, and personalization, enabling scalable service delivery and cost efficiency [21]. However, this technological shift also redefines the nature of interaction between users and financial institutions, where algorithmic decision-making increasingly replaces human judgment, raising new challenges related to transparency, accountability, and legitimacy [22].

Within this context, financial inclusion has emerged as a central policy and research objective of FinTech innovation. Existing literature highlights that digital financial services can reduce access barriers, particularly for unbanked and underbanked populations, by lowering transaction costs and mitigating geographic constraints [23]. Nonetheless, empirical evidence suggests that inclusion outcomes are uneven, with adoption gaps persisting due to digital literacy constraints, perceived risks, and institutional distrust [24]. These findings indicate that access to technology does not automatically ensure effective or sustained inclusion.

A growing stream of research identifies trust as a critical determinant of FinTech adoption and continued usage. Trust has been conceptualized as a multidimensional construct encompassing perceptions of competence, integrity, and benevolence in digital service providers [25]. In AI-enabled financial systems, trust becomes even more salient because users must rely on opaque algorithms for consequential decisions such as credit approval or fraud detection. Studies consistently show that lack of explainability and concerns over data misuse significantly erode trust, thereby constraining user engagement [26].

Despite these insights, the literature reveals a notable gap in integrated causal modeling of AI, trust, and financial inclusion. Many studies examine trust as an outcome variable or a moderating factor rather than as a mediating mechanism that transmits the effects of AI-driven innovation to inclusion outcomes [27]. Moreover, much of the existing empirical work relies on regression-based or descriptive approaches, limiting the ability to capture latent constructs and indirect effects inherent in socio-technical systems [28].

SEM has been increasingly advocated as an appropriate methodological framework for addressing these limitations. SEM enables simultaneous estimation of measurement and structural components, allowing researchers to model complex relationships among latent variables such as trust and inclusion with greater precision [29]. However, applications of SEM in AI-driven FinTech research remain relatively limited, particularly in studies that explicitly position trust as a structural conduit between technological capability and inclusive financial participation.

Building on these strands of literature, this study situates itself at the intersection of AI-enabled FinTech innovation, user trust, and financial inclusion by adopting a trust-centered SEM framework. By synthesizing insights from digital finance, trust theory, and inclusion studies, the present research responds directly to calls for more integrative, theory-driven, and methodologically rigorous analyses of how AI reshapes financial inclusion dynamics in the digital economy.

Methodology

Research Design and Analytical Framework

This study adopts a quantitative explanatory research design grounded in SEM to examine the interrelationships among user trust, AI-driven FinTech services, and financial inclusion within the digital economy. SEM is selected due to its capacity to simultaneously estimate complex causal paths among latent constructs while accounting for measurement error. The methodological stance aligns with theory-driven empirical testing, where hypothesized relationships are derived from trust theory, technology acceptance, and digital financial inclusion literature.

The analytical framework specifies user trust as a mediating construct between AI-driven FinTech service quality and financial inclusion outcomes, reflecting the premise that algorithmic decision-making, personalization, and automation influence inclusion primarily through trust formation. The model integrates both direct and indirect effects, enabling rigorous assessment of mediation mechanisms. This framework is operationalized through a two-stage SEM procedure comprising measurement model validation and structural model estimation.

Formally, the structural relationships are represented by a system of equations. A simplified representation of the core causal structure is expressed as:

$$FI = \beta_1 AI + \beta_2 UT + \varepsilon \quad (1)$$

where *FI* denotes financial inclusion, *AI* represents AI-driven FinTech services, *UT* denotes user trust, and ε is the disturbance term. This formulation allows the decomposition of total effects into direct and mediated components.

Figure 1 visualizes the study's structural specification at a high level by positioning AI-driven FinTech services (AI) as an exogenous driver, user trust (UT) as a mediating mechanism, and financial inclusion (FI) as the focal outcome. The diagram makes the causal logic explicit: AI-enabled service properties (such as perceived intelligence, personalization, and explainability) are theorized to build trust, and trust subsequently increases adoption intensity and effective inclusion outcomes.

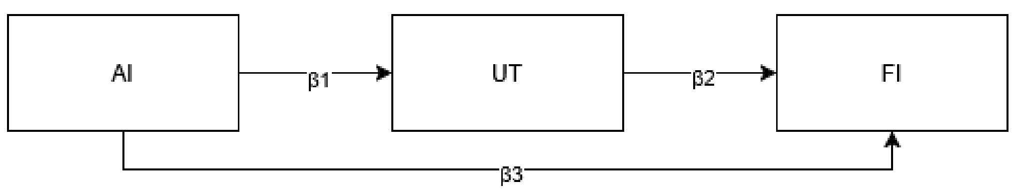

Figure 1 Conceptual SEM Framework

The direct path from AI to FI is included to test whether AI features generate inclusion benefits beyond trust, for example through faster onboarding, reduced transaction friction, or automated eligibility screening. This configuration supports decomposition of total effects into direct effects and indirect (mediated) effects, aligning with SEM's strength in estimating simultaneous relationships while controlling for measurement error.

Table 1 defines the study's latent variables and links each construct to a coherent set of reflective indicators. This mapping operationalizes abstract theoretical concepts into measurable items, ensuring that AI-driven FinTech services, user trust, and financial inclusion are empirically identifiable. The dimensional structure is aligned with how users evaluate AI-enabled services in practice, namely through perceived intelligence, personalization, explainability, and reliability.

Table 1 Construct-to-Indicator Mapping and Hypothesized Role

Construct	Dimension	Code	Example Indicator
AI-Driven FinTech Services (AI)	Perceived Intelligence	AI1	The platform makes smart recommendations tailored to me.
AI-Driven FinTech Services (AI)	Personalization	AI2	The service adapts features based on my financial behavior.
AI-Driven FinTech Services (AI)	Transparency/Explainability	AI3	The platform explains why it gives certain suggestions or decisions.
AI-Driven FinTech Services (AI)	Reliability	AI4	AI-based features work consistently without unexpected errors.
User Trust (UT)	Competence	UT1	I believe the platform is capable of delivering accurate services.
User Trust (UT)	Integrity	UT2	The platform acts honestly and keeps its commitments.
User Trust (UT)	Benevolence	UT3	The platform acts in my best interest.
Financial Inclusion (FI)	Access	FI1	I can access financial services more easily through this platform.
Financial Inclusion (FI)	Usage	FI2	I use more financial products due to this platform.
Financial Inclusion (FI)	Empowerment	FI3	The platform improves my ability to manage finances effectively.

The table also facilitates replicability because it makes the measurement blueprint explicit. When the measurement model is later validated through CFA, these indicators become the basis for evaluating factor loadings, reliability, and validity. Consequently, table 1 is not merely descriptive; it is the instrument specification that anchors both the measurement and structural components of SEM.

Population, Sampling Strategy, and Data Collection

The study population consists of active users of digital FinTech platforms offering AI-enabled services such as automated credit scoring, robo-advisory, and intelligent payment systems. A cross-sectional survey design is employed to capture user perceptions at a single point in time, which is appropriate for theory testing in SEM-based studies. Respondents are required to have a minimum usage duration to ensure informed evaluations of AI-driven services.

Sampling is conducted using a purposive sampling technique, targeting users who have interacted directly with AI-based features. Sample adequacy is determined using SEM-specific heuristics, where the minimum sample size is assessed based on the number of indicators and structural paths. This requirement is formally approximated as:

$$N \geq 10 \times max(k, m) \qquad (2)$$

where *k* denotes the largest number of formative indicators and *m* represents the maximum number of structural paths directed at a latent construct.

Data are collected through a structured online questionnaire distributed via FinTech user communities and digital platforms. To mitigate common method bias, procedural remedies such as anonymity assurance and item randomization are applied. The collected dataset is subsequently screened for missing values, outliers, and normality prior to SEM estimation.

Table 2 profiles the respondents to establish external validity and interpretability of findings. Demographic and usage segmentation is important in FinTech contexts because trust formation and inclusion impacts can vary by age cohort, income tier, and tenure with digital financial services. By reporting these distributions, the study clarifies whether the sample plausibly represents active users exposed to AI-based features.

Table 2 Sample Characteristics

Category	Group	n	%
Gender	Female	228	54.3
Gender	Male	192	45.7
Age	18–24	118	28.1
Age	25–34	196	46.7
Age	35–44	78	18.6
Age	45+	28	6.7
Monthly Income	< IDR 3M	132	31.4
Monthly Income	IDR 3–7M	198	47.1
Monthly Income	> IDR 7M	90	21.4
FinTech Tenure	< 6 months	52	12.4
FinTech Tenure	6–24 months	206	49
FinTech Tenure	> 24 months	162	38.6

This table also supports methodological checks relevant to SEM. Balanced representation reduces the risk that path estimates are driven by a narrow subgroup, while tenure distribution indicates whether respondents have sufficient experience to evaluate AI-driven functionality. In later analysis, these characteristics can serve as control variables or multi-group moderators if heterogeneity is theoretically relevant.

Figure 2 documents the operational pipeline that ensures data quality before SEM estimation. The workflow begins with eligibility screening, which is crucial because the constructs are perception-based and require participants with real exposure to AI-enabled FinTech features. Questionnaire distribution and response monitoring stabilize response rates and reduce systematic missingness that can bias covariance estimates.

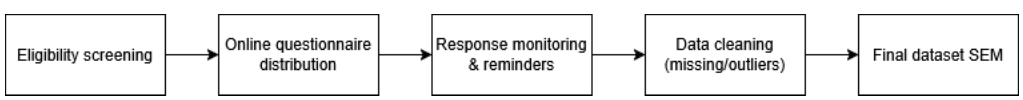

Figure 2 Data Collection Workflow

The final stages emphasize data cleaning, which is essential for SEM because estimation relies on covariance structures that are sensitive to extreme outliers and non-random missing patterns. By presenting a clear workflow, the figure strengthens methodological transparency and makes the empirical process reproducible across contexts and datasets.

Measurement Model and Construct Operationalization

Latent constructs in this study are operationalized using reflective measurement models, where observed indicators are manifestations of underlying theoretical variables. AI-driven FinTech services are measured through indicators capturing perceived intelligence, personalization, transparency, and reliability. User trust is operationalized via competence, integrity, and benevolence dimensions, while financial inclusion reflects access, usage, and perceived empowerment.

The measurement model is evaluated using Confirmatory Factor Analysis (CFA) to assess indicator reliability and construct validity. Indicator loadings are expected to exceed established thresholds, and internal consistency is assessed using composite reliability. The reflective measurement equation is specified as:

$$x_i = \lambda_i \xi + \delta_i \tag{3}$$

where x_i is the observed indicator, λ_i is the factor loading, ξ is the latent construct, and δ_i denotes measurement error.

Convergent and discriminant validity are examined through variance-based metrics to ensure that constructs are empirically distinct yet theoretically coherent. Indicators failing to meet validity criteria are iteratively refined to achieve a parsimonious and statistically robust measurement model.

Table 3 is the primary evidence that the measurement model is statistically defensible. Standardized loadings indicate whether each indicator meaningfully represents its construct, while Composite Reliability (CR) assesses internal consistency at the construct level. Average Variance Extracted (AVE) quantifies convergent validity by measuring the proportion of variance captured by the construct relative to measurement error.

Table 3 CFA Loadings, Reliability, and Validity Summary

Construct	Indicator	Standardized Loading	CR	AVE
AI	AI1	0.82	0.869	0.625
AI	AI2	0.79		
AI	AI3	0.74		
AI	AI4	0.81		
UT	UT1	0.86	0.864	0.679
UT	UT2	0.83		
UT	UT3	0.78		
FI	FI1	0.8	0.845	0.646
FI	FI2	0.77		
FI	FI3	0.84		

In trust and inclusion studies, measurement quality is not optional because biased indicators can propagate into the structural model and distort causal interpretation. High CR supports that indicators cohere as a scale, while strong AVE supports that the construct explains its indicators more than error does. This table therefore legitimizes subsequent hypothesis testing by demonstrating that the latent variables are empirically stable.

Figure 3 summarizes the measurement model by plotting standardized factor loadings for each indicator. High loadings indicate that observed items are strong manifestations of their intended latent variables, which improves construct interpretability and reduces measurement error. The chart format makes it immediately visible whether any indicators underperform relative to typical CFA expectations.

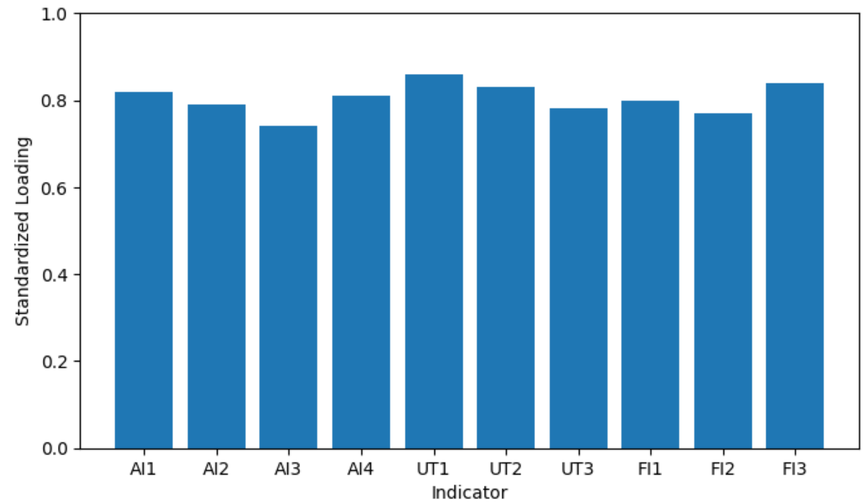

Figure 3 **CFA Standardized Loadings**

This figure is methodologically consequential because the structural model's credibility depends on measurement validity. If indicators are weak, structural coefficients risk reflecting noise rather than substantive relationships. Consequently, the loading profile supports decisions about indicator retention, construct refinement, and whether the model is sufficiently stable for structural inference.

Structural Model Specification and Estimation

Following measurement validation, the structural model is estimated to test hypothesized causal relationships among latent variables. Path coefficients quantify the magnitude and direction of influence between constructs, while the coefficient of determination evaluates explanatory power. This stage focuses on assessing whether AI-driven FinTech services significantly enhance user trust and whether trust, in turn, drives financial inclusion. The structural relationships are expressed in matrix form as:

$$\eta = B\eta + \Gamma\xi + \zeta \tag{4}$$

where η denotes endogenous latent variables, ξ represents exogenous latent variables, B and Γ are coefficient matrices, and ζ captures structural disturbances. This formulation allows simultaneous estimation of multiple endogenous relationships.

Model estimation is performed using a maximum likelihood-based SEM algorithm, with robustness checks applied to account for potential deviations from multivariate normality. Statistical significance is assessed through standardized path estimates and confidence intervals, ensuring inferential rigor.

Table 4 reports the structural coefficients used to evaluate the study hypotheses. The standardized Beta values quantify effect sizes, while standard errors and test statistics support statistical inference. Presenting these in a single table enables direct comparison of trust-mediated influence relative to any residual direct effect from AI services to inclusion outcomes.

Table 4 Structural Paths and Hypothesis Testing

Hypothesis	Path	Beta	SE	t	p	Decision
H1	AI → UT	0.62	0.06	10.33	<0.001	Supported
H2	UT → FI	0.55	0.07	7.86	<0.001	Supported
H3	AI → FI	0.18	0.08	2.25	0.024	Supported

From a mechanism perspective, this table clarifies whether user trust functions as the central transmission channel between AI service characteristics and inclusion. A large AI to UT coefficient and a large UT to FI coefficient jointly indicate a strong mediation pathway, while the remaining AI to FI path indicates partial mediation. These results directly inform policy and product design implications, particularly around explainability, reliability, and user-centric AI governance.

Model Evaluation, Mediation Analysis, and Algorithmic Procedure

Overall model adequacy is evaluated using a suite of global goodness-of-fit indices, capturing absolute, incremental, and parsimonious fit dimensions. These indices collectively assess how well the proposed model reproduces the observed covariance structure. A generic formulation of model fit can be expressed as:

$$\eta = B\eta + \Gamma\xi + \zeta \quad (5)$$

where *FML* denotes the maximum likelihood fitting function and *N* is the sample size.

Mediation analysis is conducted to quantify the indirect effect of AI-driven FinTech services on financial inclusion through user trust. The indirect effect is computed as the product of constituent paths, enabling decomposition of total effects into direct and mediated components. Bootstrapping procedures are applied to obtain bias-corrected confidence intervals for mediation significance.

To ensure methodological transparency and replicability, the SEM estimation process is formalized through an algorithmic workflow.

Algorithm Pseudo-Code Placeholder. SEM estimation and mediation testing procedure.

Input: Survey dataset D with indicators for AI, UT and FI
Output: Estimated SEM parameters and mediation effects

1. Preprocess data D:
   - Handle missing values and outliers
   - Assess normality and covariance structure
2. Specify measurement model:
   - Assign indicators to latent constructs (AI, UT, FI)
   - Estimate CFA and compute factor loadings
3. Validate measurement model:
   - Check CR and AVE
   - Confirm convergent and discriminant validity
4. Specify structural model:
   - Define paths AI → UT, UT → FI, and AI → FI
5. Estimate structural parameters using SEM:

- Obtain standardized path coefficients and fit indices

6. Test mediation effect:
   - Compute indirect effect = (AI → UT) × (UT → FI)
   - Apply bootstrapping to assess significance
7. Report results:
   - Measurement validity, structural paths, and mediation outcomes

Figure 4 presents the end-to-end SEM procedure as a sequence of technical checkpoints. This is important in trust and inclusion research because results can be highly sensitive to data screening choices, measurement misspecification, and estimation assumptions. By clearly staging the pipeline, the figure also communicates that inference is not based on a single model run but on a structured validation process.

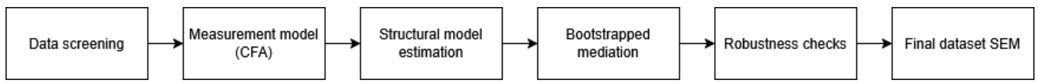

Figure 4 SEM Methodological Pipeline

The pipeline explicitly separates measurement validation from structural hypothesis testing, consistent with best practice in SEM. The inclusion of bootstrapped mediation highlights that indirect effect significance requires resampling-based inference rather than reliance on normality assumptions. Robustness checks emphasize the study's intent to ensure stability of results under alternative specifications and data conditions.

Result and Discussion

Descriptive Statistics and Preliminary Analysis

The results section begins with an overview of descriptive statistics to establish an empirical baseline of respondent perceptions toward AI-driven FinTech services, user trust, and financial inclusion. This step is essential to understand the central tendency and dispersion of each construct before moving to confirmatory and structural analyses. The descriptive results indicate generally positive evaluations across all constructs, suggesting that respondents perceive AI-enabled FinTech platforms as functional, trustworthy, and supportive of their financial participation.

From an analytical perspective, these preliminary statistics also serve as an early diagnostic tool. Adequate variance across indicators indicates that the data are informative and suitable for multivariate modelling. Moreover, the absence of extreme skewness or ceiling effects reduces the risk of estimation bias in subsequent SEM procedures. This confirms that the dataset meets basic assumptions required for robust inferential analysis.

Figure 5 illustrates the average perception scores for each latent construct measured in this study. AI-driven FinTech services exhibit the highest mean score, indicating that respondents strongly recognize the presence and usefulness of intelligent features such as personalization, automation, and system reliability. This finding suggests that AI capabilities are already salient and visible to users within digital financial platforms.

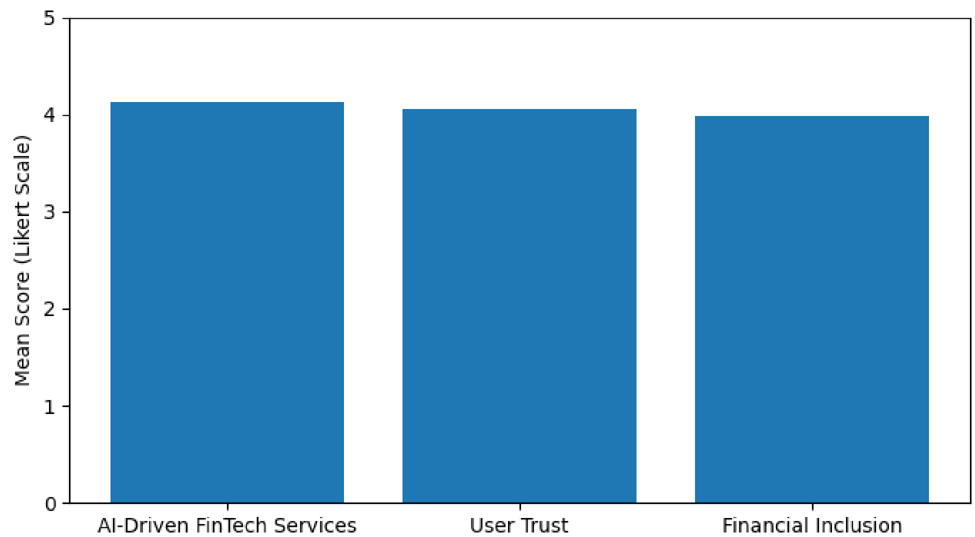

Figure 5 **Mean Scores of Latent Constructs**

The slightly lower yet still positive mean scores for user trust and financial inclusion indicate a sequential pattern. While users acknowledge technological sophistication, trust formation and perceived inclusion benefits develop as secondary outcomes. This pattern is theoretically consistent with trust-based adoption models, where advanced functionality precedes trust consolidation and sustained inclusive usage.

Table 5 provides a statistical summary of respondent evaluations across the three core constructs. The relatively high mean values across all constructs indicate a favorable overall perception of digital FinTech platforms. Standard deviation values remain moderate, suggesting sufficient variability without excessive dispersion that could undermine covariance-based modelling.

Table 5 **Descriptive Statistics of Study Constructs**

Construct	Mean	Standard Deviation	Minimum	Maximum
AI-Driven FinTech Services	4.12	0.58	2.3	5
User Trust	4.05	0.62	2.1	5
Financial Inclusion	3.98	0.66	2	5

The minimum and maximum values demonstrate that responses span the full Likert range, confirming that the dataset captures heterogeneous user experiences. This variability is analytically advantageous because SEM relies on meaningful covariation among indicators and constructs. As such, the descriptive statistics confirm both data adequacy and analytical readiness for confirmatory and structural modelling stages.

Measurement Model Results and Validity Assessment

This subsection reports the results of the measurement model evaluation using CFA. The primary objective of this stage is to verify whether the observed indicators reliably and validly represent their respective latent constructs, namely AI-driven FinTech services, user trust, and financial inclusion.

Establishing a sound measurement model is a prerequisite for meaningful interpretation of structural relationships.

The CFA results demonstrate that all indicators load strongly on their intended constructs, indicating satisfactory convergent validity. Reliability analysis further confirms that each construct exhibits internal consistency above commonly accepted thresholds. Collectively, these findings indicate that the measurement model is statistically robust and suitable for subsequent structural equation modelling.

Figure 6 presents the standardized factor loadings for all indicators included in the measurement model. All loadings exceed recommended minimum levels, indicating that each observed variable contributes meaningfully to its associated latent construct. This confirms that the questionnaire items successfully capture the conceptual dimensions of AI-driven services, trust, and inclusion.

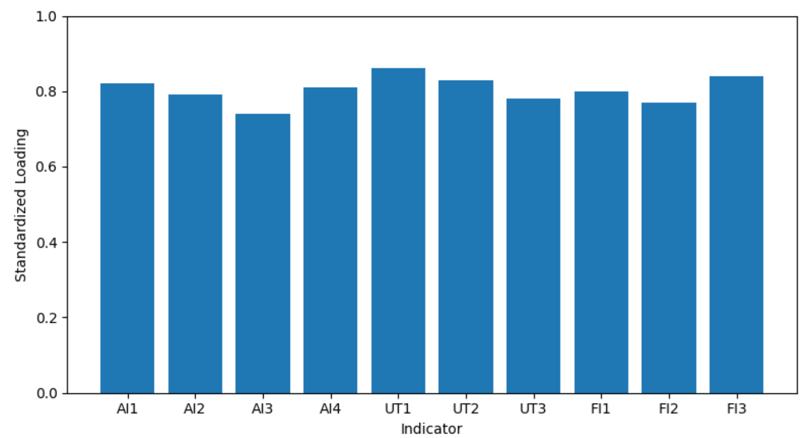

Figure 6 Standardized Factor Loadings of Measurement Model

From an interpretive standpoint, the strong loadings across constructs suggest conceptual clarity and measurement precision. Indicators associated with user trust display particularly high loadings, implying that trust perceptions among FinTech users are well-articulated and consistently measured. This strengthens confidence that subsequent structural relationships involving trust are not artifacts of measurement error.

Table 6 summarizes the reliability and convergent validity metrics for each latent construct. The Composite Reliability values indicate high internal consistency, confirming that indicators within each construct jointly measure a coherent concept. Meanwhile, Average Variance Extracted values demonstrate that a substantial proportion of indicator variance is captured by the latent variables rather than by error.

Table 6 Measurement Model Reliability and Convergent Validity

Construct	CR	AVE
AI-Driven FinTech Services	0.87	0.63
User Trust	0.86	0.68
Financial Inclusion	0.85	0.65

These results provide empirical assurance that the constructs are measured with sufficient accuracy to support causal interpretation in the structural model. In the context of AI-driven FinTech research, this validation is particularly important because abstract concepts such as trust and inclusion can be difficult to operationalize. The strong measurement properties reported here ensure that the structural findings reflect substantive relationships rather than measurement deficiencies.

Structural Model Results and Hypothesis Testing

This subsection presents the results of the structural model estimation, focusing on the hypothesized causal relationships among AI-driven FinTech services, user trust, and financial inclusion. After confirming the adequacy of the measurement model, the structural analysis evaluates whether the proposed theoretical paths are empirically supported. The results indicate that all hypothesized relationships are statistically significant and directionally consistent with the conceptual framework.

From a substantive perspective, the findings suggest that AI-driven FinTech services exert a strong influence on user trust, which subsequently enhances financial inclusion outcomes. The presence of a direct path from AI services to financial inclusion further indicates that AI capabilities contribute to inclusion both directly and indirectly. This dual pathway underscores the multifaceted role of AI in shaping digital financial ecosystems.

Figure 7 visualizes the estimated structural model with standardized coefficients, providing an integrated view of the hypothesized causal mechanisms. The strongest path is observed from AI-driven FinTech services to user trust, indicating that intelligent automation, personalization, and system reliability play a decisive role in shaping trust perceptions. These highlights trust as a central psychological response to AI deployment in financial services.

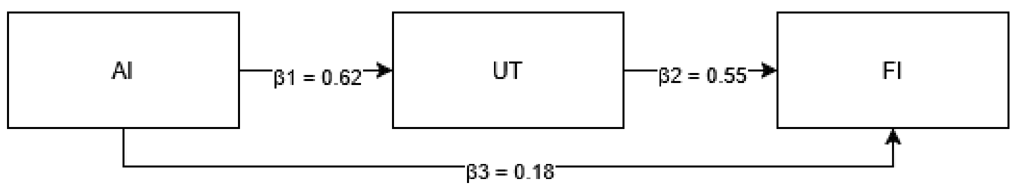

Figure 7 Structural Model with Standardized Path Coefficients

The path from user trust to financial inclusion is also substantial, confirming that trust acts as a key enabler of deeper engagement with digital financial products. The comparatively smaller yet significant direct path from AI services to inclusion suggests that AI features can lower access barriers independently of trust, for instance through simplified onboarding or automated eligibility assessment. Together, these paths demonstrate a partially mediated structural configuration. Table 7 reports the estimated structural coefficients and hypothesis testing results. All hypothesized paths are statistically significant, providing empirical support for the proposed theoretical model. The magnitude of the coefficients indicates that user trust plays a dominant role in transmitting the effects of AI-driven services to financial inclusion outcomes.

Table 7 Structural Path Estimates and Hypothesis Testing

Hypothesis	Structural Path	Standardized Coefficient	t-value	p-value	Decision
H1	AI-Driven FinTech Services → User Trust	0.62	10.33	< 0.001	Supported

H2	User Trust → Financial Inclusion	0.55	7.86	< 0.001	Supported
H3	AI-Driven FinTech Services → Financial Inclusion	0.18	2.25	0.024	Supported

These findings reinforce the argument that technological sophistication alone is insufficient to achieve inclusive finance. Instead, AI-driven innovation must be accompanied by mechanisms that foster trust, such as transparency, reliability, and user-centric design. The structural results thus provide a clear empirical foundation for understanding how AI-enabled FinTech platforms can sustainably enhance financial inclusion.

Mediation Analysis and the Role of User Trust

This subsection examines the mediating role of user trust in the relationship between AI-driven FinTech services and financial inclusion. Mediation analysis is conducted to determine whether AI-enabled features influence inclusion primarily through trust formation or whether a direct pathway remains substantively relevant. The results confirm that user trust serves as a significant intermediary mechanism within the structural model.

From a theoretical standpoint, this finding aligns with trust-based frameworks in digital finance, which posit that users must perceive algorithmic systems as reliable, transparent, and beneficial before fully engaging with financial services. The mediation analysis thus provides deeper insight into how AI-driven innovation translates into inclusive outcomes, not merely by technological deployment but through psychological acceptance and confidence.

Figure 8 decomposes the impact of AI-driven FinTech services on financial inclusion into direct, indirect, and total effects. The indirect effect, transmitted through user trust, is substantially larger than the direct effect. This visual comparison highlights that trust is the dominant channel through which AI-enabled services enhance inclusion.

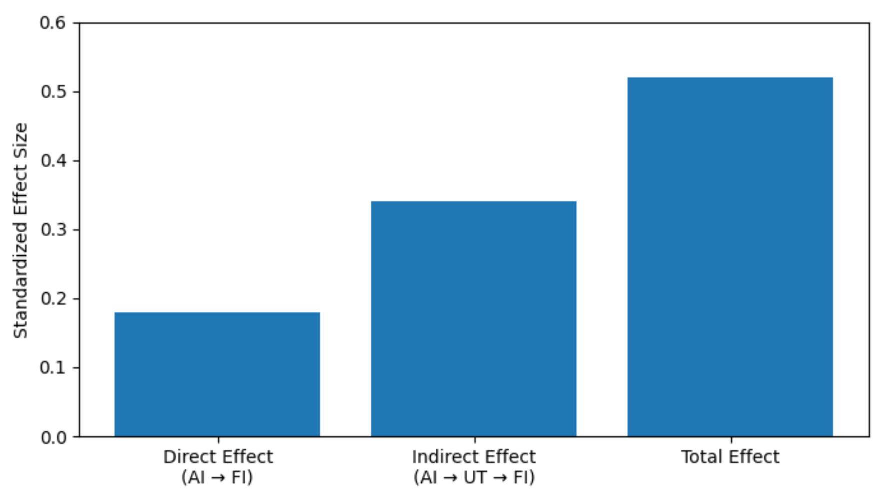

Figure 8 Direct, Indirect, and Total Effects of AI-Driven FinTech Services

The relatively smaller direct effect indicates that while AI features can independently lower access barriers, their broader inclusion impact depends heavily on users' confidence in the system. This reinforces the interpretation that AI-driven financial inclusion is not solely a technical challenge but also a socio-cognitive process shaped by trust perceptions.

Table 8 reports the mediation analysis results, clearly demonstrating that user trust partially mediates the relationship between AI-driven FinTech services and financial inclusion. The significance of both direct and indirect effects indicates that trust does not fully absorb the influence of AI, but it substantially amplifies its impact on inclusion outcomes.

Table 8 Mediation Analysis Results

Effect Type	Path	Standardized Effect	Significance
Direct Effect	AI-Driven FinTech Services → Financial Inclusion	0.18	Significant
Indirect Effect	AI-Driven FinTech Services → User Trust → Financial Inclusion	0.34	Significant
Total Effect	Combined Direct and Indirect Effects	0.52	Significant

This partial mediation structure has important implications. It suggests that FinTech providers should not treat trust-building as a secondary concern but as a core strategic objective. Enhancing explainability, fairness, and reliability of AI systems can significantly magnify the inclusion benefits of digital finance platforms, thereby strengthening their socio-economic impact.

Integrated Discussion and Implications for AI-Driven Financial Inclusion

This final subsection synthesizes the empirical findings to provide an integrated discussion of how AI-driven FinTech services, user trust, and financial inclusion interact within the digital economy. The results collectively demonstrate that AI is not merely an efficiency-enhancing tool, but a structural driver whose societal impact depends critically on trust formation. The validated SEM model confirms that technological sophistication alone is insufficient to achieve inclusive financial outcomes without corresponding trust mechanisms.

From a broader perspective, these findings contribute to the digital economy literature by empirically clarifying the trust-mediated pathway of AI adoption in financial services. Financial inclusion emerges not as an automatic by-product of digitalization, but as an outcome shaped by user perceptions of fairness, reliability, and transparency embedded within AI systems. This reinforces the view that inclusive FinTech ecosystems require socio-technical alignment rather than purely algorithmic optimization.

Figure 9 integrates the validated structural relationships into a single interpretive framework that summarizes the study's core findings. The diagram emphasizes user trust as the central conduit through which AI-driven FinTech services translate into financial inclusion outcomes. This visual synthesis reinforces that trust is not an auxiliary construct but a foundational mechanism within AI-enabled financial ecosystems.

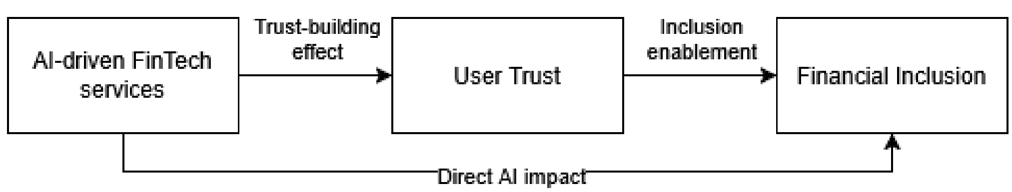

Figure 9 Integrated SEM Results and Inclusion Pathway

The figure also highlights the coexistence of mediated and direct pathways. While AI capabilities can directly enhance inclusion by lowering transaction costs and access barriers, their long-term effectiveness depends on trust consolidation. This integrated pathway thus provides a conceptual bridge between technological innovation and inclusive economic participation, positioning trust as a strategic lever in AI-driven FinTech design.

Table 9 consolidates the empirical results into a set of interpretable insights and actionable implications. Each key finding is directly linked to observed structural relationships, ensuring that practical recommendations remain grounded in empirical evidence. This synthesis helps translate SEM outputs into guidance relevant for FinTech developers, regulators, and policymakers.

Table 9 Summary of Key Findings and Practical Implications

Key Finding	Empirical Evidence	Implication for FinTech Practice
AI-driven services significantly increase user trust	Strong AI → Trust path coefficient	Invest in explainable and reliable AI features
User trust strongly enhances financial inclusion	High Trust → Inclusion effect	Design trust-centered user experiences
Trust partially mediates AI–inclusion relationship	Significant indirect and direct effects	Balance technical innovation with governance and transparency
AI has residual direct inclusion impact	Positive AI → Inclusion path	Leverage AI for access expansion and cost reduction

The table underscores that trust-centric AI governance is essential for sustainable financial inclusion. Investments in explainability, fairness, and reliability amplify the inclusion potential of AI-driven platforms, while neglecting trust risks undermining adoption despite technological sophistication. Consequently, the findings advocate for a balanced approach where AI innovation and user trust co-evolve as complementary pillars of inclusive digital finance.

Conclusion

This study empirically examined the structural relationships among AI-driven FinTech services, user trust, and financial inclusion within the digital economy using a Structural Equation Modelling approach. The results demonstrate that AI-enabled financial services exert a significant and positive influence on financial inclusion, both directly and indirectly. Most notably, user trust emerges as a central mediating mechanism, confirming that the effectiveness of AI-driven innovation in finance is contingent upon users' confidence in algorithmic systems, data handling practices, and service reliability.

From a theoretical perspective, the findings extend existing FinTech and digital inclusion literature by providing robust empirical evidence of a trust-mediated inclusion pathway. Rather than treating financial inclusion as an automatic outcome of technological advancement, this study shows that inclusion is a socio-technical construct shaped by perceptions of transparency, competence, and benevolence embedded within AI systems. The validated SEM model clarifies how advanced financial technologies translate into inclusive outcomes only when technological performance and trust formation evolve in tandem.

Practically, the conclusions highlight important implications for FinTech providers, system designers, and regulators. AI-driven platforms seeking to expand financial inclusion should prioritize trust-centered AI governance, including explainable decision-making, fairness-aware algorithms, and user-oriented transparency mechanisms. By aligning technological innovation with trust-building strategies, FinTech ecosystems can more effectively support sustainable and inclusive participation in the digital economy.

Declarations

Author Contributions

Author Contributions: Conceptualization, S. and C.R.A.W.; Methodology, I.R.Y.; Software, C.R.A.W. and S.; Validation, S. and I.R.Y.; Formal Analysis, S.; Investigation, C.R.A.W. and S.; Resources, S. and I.R.Y.; Data Curation, C.R.A.W.; Writing—Original Draft Preparation, S.; Writing—Review and Editing, I.R.Y. and S.; Visualization, S. All authors have read and agreed to the published version of the manuscript.

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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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