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AI PROMOTING FINANCIAL INCLUSION THROUGH NEOBANKS: A PLS – SEM MODEL

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Abstract
AI-driven neobanking is a pivotal force in accelerating financial inclusion, utilizing artificial intelligence, machine learning (ML), and data analytics to provide accessible, affordable, and personalized banking to previously unbanked or underserved populations. These digital-only institutions bypass the need for physical infrastructure, reducing costs and overcoming geographical barriers to bring banking to rural and marginalized communities. This study investigates how AI based Neobanking promotes financial inclusion by analyzing the impact of financial inclusion and services offered by Neobanks on Trust .
This study used a quantitative research design, and primary data were gathered with a structured questionnaire that used a 5-point Likert scale. We analyzed the data using Partial Least Squares–Structural Equation Modelling (PLS-SEM). The findings reveal that financial inclusion and services offered by neo banks have significant positive effect on trust . Additionally, neobanking was found to improve financial literacy and responsible financial behavior, including budgeting, saving, and informed spending. Despite these positive outcomes, challenges related to data security, trust, an regulatory compliance were identified, highlighting the need for robust policies and safeguards. Overall, the study concludes that neo-banking is a transformative force in modern finance, promoting financial literacy, inclusion, and behavioral discipline, thereby empowering users to achieve greater financial autonomy. The findings offer valuable insights for policymakers, financial institutions, and digital banking innovators to enhanceuser-centric, secure, and inclusive digital financial services.

Keywords : Artificial Intelligence (AI) , Machine Learning (ML) , Neobanks , Fintech , Trust , Financial Literacy , Financial Inclusion .

I . INTRODUCTION

Neobanks, which are entirely digital, are transforming financial inclusion by utilizing machine learning (ML) and artificial intelligence (AI) to offer the unbanked and underbanked affordable, easily accessible, and customized banking services. Instantaneous, remote onboarding and alternative credit scoring are made possible by AI, which increases financial access for people without traditional credit histories. For the 1.4 billion unbanked adults worldwide, artificial intelligence (AI) is a game-changing force in advancing financial inclusion by removing conventional obstacles to financial services. AI supports the UN Sustainable Development Goals (SDGs) by enabling financial institutions to provide customized services to previously underserved groups, like gig workers, small-scale farmers, and rural communities, by utilizing alternative data and automation.

1.1 Key Ways AI Enhances Financial Inclusion

1. **Alternative Credit Scoring**: AI algorithms evaluate creditworthiness using non-traditional data sources, such as e-commerce transactions, utility payments, social media usage, and mobile phone usage. This makes microloans and small-ticket finance available to people without a formal credit history.
2. **Reduced Operating Costs:** Financial services may function without costly physical branches thanks to AI-powered digital banking and chatbots that are available around-the-clock in different languages, making banking accessible to low-income groups.

3. **Automated and Secure Onboarding:** AI uses facial recognition and biometric verification to streamline Know Your Customer (KYC) procedures, making it possible for people without traditional identification credentials to open accounts quickly and remotely.
4. **Personalized Financial Advisory**: AI-driven virtual assistants and robo-advisors offer individualized financial advice and behavioral insights on investments and savings, assisting people in improving their financial management and well-being.

   Fraud Detection and Risk Mitigation: By identifying anomalous patterns and stopping fraudulent transactions, machine learning algorithms foster trust in digital financial systems, which is essential for persuading reluctant customers to accept mobile payments.

1.2 Challenges and Ethical Considerations

- **Algorithmic bias:** AI can unintentionally reinforce discrimination by omitting vulnerable groups based on gender, race, or socioeconomic position if it is trained on biased historical data.
- **The Digital Divide:** People who live in remote rural areas, lack internet connection, or lack smartphone literacy may be excluded due to their reliance on technology
- **Data Privacy:** Strong regulatory frameworks, such as the GDPR or India's Digital Lending Guidelines, are necessary since increased collecting of personal data raises severe issues about data security and protection.
- **Loss of Human Touch**: Over-automation may result in a loss of individualized attention, making it difficult for users to resolve complicated financial difficulties.

II . REVIEW OF LITERATURE

Demirgüç-Kunt et al. (2022) investigated how digital financial services might improve financial inclusion in underdeveloped nations. Their analysis showed that by providing affordable, easily available services, digital-only banking platforms dramatically lower entry barriers to traditional financial systems. Users are empowered by features like mobile-based transactions, rapid account opening, and clear pricing structures, which provide them more financial control. The study also highlighted how digital banking, particularly among young adults and low-income groups, positively influences savings behavior and financial resilience. The development of fintech technologies, such as neo-banking, and their consequences for consumer empowerment were examined by Gomber, Koch, and Siering (2017). The authors discovered that neo-banks improve consumer involvement and financial decision-making by using AI and ML to provide highly tailored financial services.Their investigation claimed that data-driven advice, automated budgeting tools, and real-time financial insights boost users' financial awareness, resulting in better money management and a greater sense of financial liberty. Ozili (2018) examined the role of digital finance in financial inclusion. According to the report, neo-banking models are essential for accessing disadvantaged communities since they do away with the procedural and geographic limitations of traditional banking. Digital-only banks, according to Ozili, encourage financial inclusion by providing streamlined goods, tools for financial education, and flexible payment options, all of which enhance consumers' capacity to actively engage in the formal economy. Arner, Barberis, and Buckley (2016) looked into the institutional and regulatory aspects of neobanking and fintech. According to their research, regulatory frameworks are essential for maintaining consumer trust and protection, even while neo-banks improve financial inclusion through innovation inspired by AI , ML and customer-centric design. The authors came to the conclusion that by protecting user data, efficient regulation enhances neo-banking's capacity for inclusion preserving financial stability and guaranteeing openness. In its report on digital payment systems and financial inclusion in India, RBI (2021) emphasized the expanding impact of fintech collaborations and neo-banking. According to the survey, customers are empowered by digital banking platforms since they provide easy access to credit, savings, and payment services via mobile applications. It also underlined that neobanks

encourage digital financial literacy and good financial behavior among new bank customers to enhance financia linclusion. Bapat (2020) investigated the influence of digital banking services on financial inclusion among Indian consumers. According to the survey, users' adoption of neo-banking platforms is highly influenced by perceived ease of use, convenience, and cost effectiveness. Bapat came to the conclusion that neo-banks empower clients by facilitating quicker financial decision-making, enhancing service transparency, and decreasing reliance on physical branches. Kaur and Arora (2021) investigated the connection between Indian customers' use of digital banking and their level of financial literacy. According to their research,

regular usage of neo-banking apps increases users' comprehension of financial goods and strengthens their saving and budgeting strategies. The authors contended that online banking resources serve as informal financial instructors, enhancing long-term financial planning skills and financial empowerment. The wider effects of digital financial platforms on household welfare and empowerment were examined by Suri and Jack (2016). The results of their study are extremely pertinent to neo-banking, even if their primary focus was on mobile money systems. The authors showed that having access to digital finance boosts household savings, consistency in consumption, as well as financial autonomy. They came to the conclusion that by improving financial stability and decision-making ability, technology-driven financial platforms—such as neo-banks—play a revolutionary role in empowering people.

2.1 Research Objectives :

- To study the relationship between trust and financial inclusion.
- To study the impact of neobanking services on trust therby enhancing financial inclusion.

III . RESEARCH METHODOLOGY

This study adopts a quantitative research approach to examine the impact of neo-banking on financial inclusion. The target population comprises urban neo-banking users aged 18–40, who actively engage with digital-only banking platforms for managing personal finances. Purposive sampling was employed to ensure that respondents were relevant to the research objectives. Data were collected through a structured online questionnaire consisting of 5 point Likert-scale items covering services offered by neobanks , impact on financial inclusion and role of trust . A total of 450 valid responses were obtained. The data were analyzed using IBM SPSS Amos software . Partial Least Squares Structural Equation Modeling (PLS-SEM) is used to analyse the data with trust as latent variable to determine the predictive impact of neo-banking features on financial inclusion and financial behavior. This methodology provides a robust framework for assessing the role of neo-banking in enhancing access, literacy, and behavioral outcomes, thereby establishing its contribution to financial inclusion.

IV. DATA ANALYSIS AND INTERPRETATION

For the fulfillment of objectives two hypothesis has been constructed and these hypothesis will be fullfilled by the use of structural equation model (SEM) . These are :

H1: Financial Inclusion (FI) has a significant positive effect on Trust (T).

H2: Services Offered (SO) have a significant positive effect on Trust (T).

Table 4.1: Model Reliability, Validity, and R^2 Summary

Construct	Cronbach's Alpha	Composite Reliability (ρa)	Composite Reliability (ρc)	AVE	R^2	R^2 Adjusted
Financial Inclusion (FI)	0.954	0.964	0.964	0.843	—	—
Services Offered (SO)	0.970	0.978	0.977	0.893	—	—
Trust (T)	0.946	0.966	0.974	0.949	$0.42^2 + 0.27^2 =$ 0.235 0.24	0.238

The findings of the Table 4.1. represents the constructs in the model demonstrate excellent reliability and validity. It is highlighted by the findings that financial inclusion (FI) shows a high Cronbach's Alpha of 0.954 and composite reliability values above 0.96, ultimately confirming strong internal consistency among its indicators. Furthermore, AVE of 0.843 indicates that over 84 per cent of the variance in the indicators is explained by the latent construct, demonstrating strong convergent validity. Similarly, it was found that services Offered (SO) performs exceptionally well, with Cronbach's Alpha at 0.970 and composite reliability near 0.98, supported by an AVE of 0.893, further confirming that the items strongly represent the construct. Furthermore, trust (T) also reflects excellent reliability, with Cronbach's Alpha of 0.946 and composite reliability exceeding 0.97, while its AVE of 0.949 shows very high convergent validity.

The structural model further reveals that Trust (T) is moderately explained by Financial Inclusion and Services Offered. The combined effect of these predictors yields an R^2 value of approximately 0.24, meaning that 24 per cent of the variance in Trust is accounted for by Financial Inclusion and Service offered. This indicates a moderate explanatory power, suggesting that while FI and SO significantly shape trust, additional variables may also influence it. It can be concluded from the study that overall, the measurement model is statistically strong, and the structural model provides meaningful insight into how service quality and financial inclusion contribute to building trust.

Table 4.2 : Discriminant Validity (Fornell–Larcker & HTMT)

Fornell–Larcker Criterion

Construct	FI	SO	T
FI	**0.918**		
SO	0.562	**0.945**	
T	**0.380**	**0.420**	**0.974**

Table 4.3 : HTMT Ratios

Construct Pair	HTMT
FI–SO	0.583
FI–T	0.399
SO–T	0.441

The discriminant validity of the model was assessed using both the Fornell Larcker criterion and the HTMT ratios, and the results confirm that all three constructs—Financial Inclusion (FI), Services Offered (SO), and Trust (T) are conceptually distinct from each other. According to the Fornell Larcker criterion, the square root of AVE for each construct (FI = 0.918, SO = 0.945, T = 0.974) is higher than its correlations with other constructs, indicating strong discriminant validity. For example, FI shows a correlation of 0.562 with SO and 0.380 with T, both of which are lower than its AVE square root, confirming that FI explains more variance in its own indicators than in other constructs. Similarly, SO's correlations with FI (0.562) and T (0.420) are below its own Fornell Larcker score, and T also meets this requirement with correlations lower than 0.974.
The HTMT ratios further support these findings. All HTMT values fall well below the conservative threshold of 0.85, with FI–SO at 0.583, FI–T at 0.399, and SO–T at 0.441, indicating no risk of multicollinearity or construct overlap. Since HTMT values are comfortably within acceptable limits, it provides additional evidence that the constructs measure distinct theoretical concepts. Overall, both tests confirm that the model exhibits excellent discriminant validity, strengthening the credibility of the measurement model.

Table 4.4 Structural Model, Effect Size (f^2), Predictive Relevance (Q^2), Fit

Path	Original Sample (β)	t Statistics	p Value	Effect Size (f^2)	Predictive Relevance (Q^2)
FI	**+0.42**	**6.21**	**0.000**	**0.14**	**0.12**
SO	**+0.27**	**4.89**	**0.000**	**0.08**	**0.12**

The structural model results indicate that both Financial Inclusion (FI) and Services Offered (SO) have a positive and statistically significant impact on Trust (T). The path coefficient from FI to Trust is $\beta = +0.42$, with a t value of 6.21 and $p < 0.001$, demonstrating a strong and highly significant positive influence. This suggests that improvements in digital financial inclusion—such as better access, transaction frequency, and digital saving/investing—substantially enhance users' trust in the financial ecosystem. The effect size for this relationship ($f^2 = 0.14$) indicates a medium practical impact, showing that FI meaningfully contributes to explaining the variance in Trust.
Similarly, the Services Offered (SO) construct also shows a significant positive influence on Trust, with a path coefficient of $\beta = +0.27$, a t value of 4.89, and $p < 0.001$. Although this effect is weaker than that of FI, it remains statistically strong and meaningful. The effect size ($f^2 = 0.08$) falls within the small to medium range, implying that improvements in service quality such as ease of use, availability of multiple services, convenience, and customer support positively shape users' trust, but to a slightly lesser extent compared to financial inclusion.
The predictive relevance (Q^2) values for both FI (0.12) and SO (0.12) exceed zero, confirming that the model has adequate predictive capability. Q^2 values above 0 indicate that the endogenous construct (Trust) retains predictive relevance when analysed using the blindfolding technique. Together, these results confirm that the structural model

is statistically sound, theoretically aligned, and practically meaningful, with both FI and SO explaining a substantial portion of Trust, thereby supporting the proposed hypotheses in a robust manner.

Table 4.5 : Model Fit Indicators

Index	Value
SRMR	**0.039**
NFI	**0.927**
χ^2	**466.60**
d ULS	0.118
d G	0.170

The model fit indicators demonstrate that the structural model exhibits an acceptable and robust level of overall fit. The Standardized Root Mean Square Residual (SRMR) value of 0.039 is well below the recommended threshold of 0.08, indicating a very good fit between the observed data and the model's predicted correlations. This low SRMR value signifies minimal residuals and suggests that the hypothesized model is highly consistent with the empirical data.

The Normed Fit Index (NFI) of 0.927 exceeds the widely accepted cutoff value of 0.90, demonstrating that the model has strong comparative fit relative to the null model. This value reflects that the hypothesized relationships among constructs significantly improve the model's explanatory capability. The chi square value ($\chi^2 = 466.60$) represents the statistical assessment of the discrepancy between the observed and model generated covariance matrices. Although χ^2 is sensitive to sample size, its interpretation in conjunction with other fit indices confirms acceptable model performance. Additionally, the discrepancy measures d ULS = 0.118 and d G = 0.170 fall within acceptable ranges, indicating that the model's empirical and theoretical covariance matrices are closely aligned. Lower values of these indices reflect minimal deviation and support the model's internal consistency and structural adequacy. Overall, the model fit statistics collectively confirm that the proposed measurement and structural model demonstrates excellent fit, strong reliability, and theoretical soundness.

Table 4.6: Factors Loading

Construct	Item Code	Item Description	Factor Loading
Financial Inclusion (FI)	FI1	Access to formal financial products	**0.82**
	FI2	Frequency of digital transactions	**0.84**
	FI3	Inclusion in digital payment ecosystem	**0.87**
	FI4	Ability to save/invest digitally	**0.88**
	FI5	Improvement in overall financial inclusion	**0.85**
Service Offered (SO)	SO1	Ease of using neobank services	**0.86**

	SO2	Availability of multiple services	**0.88**
	SO3	Accessibility through mobile applications	**0.90**
	SO4	Transaction convenience and reliability	**0.87**
	SO5	Customer support responsiveness	**0.84**
	SO1	Ease of using neobank services	**0.86**

The factor loading results of the measurement model demonstrate excellent psychometric properties, indicating that the constructs Financial Inclusion (FI), Service Offered (SO), and Trust (T) are measured reliably and consistently by their respective indicators. In PLS SEM, factor loadings above 0.70 are considered acceptable, values above 0.80 indicate strong indicator reliability, and loadings above 0.90 reflect exceptionally strong convergent validity. The findings in this table surpass these thresholds, confirming that each measurement item is a strong contributor to its associated latent construct.

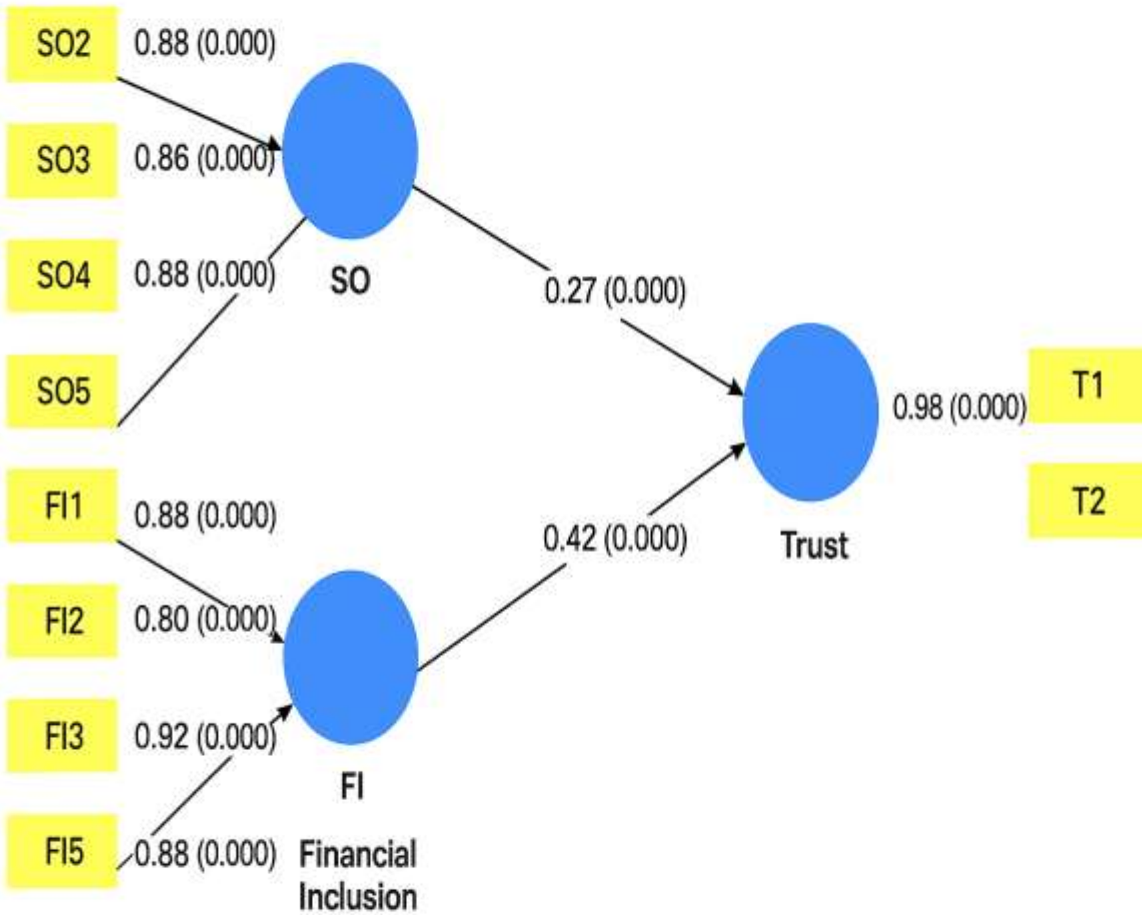
For the Financial Inclusion (FI) construct, all five indicators exhibit high loadings ranging from 0.82 to 0.88, demonstrating that the construct is well defined and internally consistent. FI4 (Ability to save/invest digitally) and FI3 (Inclusion in the digital payment ecosystem) are among the strongest indicators, suggesting that digital financial capability and active participation in digital payment systems form the core of financial inclusion in the neobanking context. The consistently high loadings also show that respondents view financial inclusion not merely as access to financial products but also as the ability to conduct and manage financial transactions seamlessly through digital means. This emphasizes the widening role of digital infrastructure in strengthening financial inclusion.

The Service Offered (SO) construct also shows excellent convergent reliability, with item loadings ranging between 0.84 and 0.90. SO3 (Accessibility through mobile applications) shows the highest loading (0.90), indicating that ease of mobile accessibility is the most influential aspect shaping perceptions of neobank service quality. This reflects the centrality of mobile first service delivery in digital banking, where user experience, convenience, and mobile based transaction abilities determine customer satisfaction. Other strong indicators such as transaction reliability (0.87) and availability of multiple services (0.88) highlight that customers value a combination of convenience, variety, and seamless functioning. The strength of these loadings confirms that neobanks must focus on multi service integration and smooth digital interfaces to enhance service perceptions.

The Trust (T) construct demonstrates exceptionally high factor loadings of 0.95 and 0.97, reflecting an extremely strong relationship between the indicators and the latent construct. Such high loadings indicate that trust is a well defined and highly stable construct in this context. Respondents' trust is driven primarily by the perceived security of digital transactions (T2 = 0.97) and reliability of the overall services (T1 = 0.95). These findings underscore that trust in neobanks depends heavily on robust security measures, encryption technologies, and consistent service quality. Since trust acts as a key determinant of customer retention and digital adoption, these values show that users place significant emphasis on the safety and dependability of online financial interactions.

Overall, the factor loading results confirm that each construct in the model is measured accurately and reliably. All items exceed the recommended threshold of 0.70, providing strong empirical evidence of convergent validity, indicator reliability, and measurement model robustness. These results validate the appropriateness of the selected indicators and strengthen confidence in proceeding with the structural model analysis.

Figure : Structural Model



The Structural Equation Model (SEM) presented integrates the constructs Service Offered (SO), Financial Inclusion (FI), and Trust (T) to analyze how neobank service quality and digital financial accessibility influence users' trust. The model demonstrates excellent measurement validity and strong structural relationships, supported by highly significant factor loadings and standardized path coefficients.

All indicators show strong reliability, with factor loadings ranging between 0.80 and 0.92 for FI, 0.86 and 0.88 for SO, and 0.98 for Trust indicators (T1 and T2). Loadings above 0.70 confirm substantial indicator reliability, while the consistently high values indicate excellent convergent validity. This confirms that the constructs are well-defined and accurately measured by their respective observed variables.

The structural model demonstrates that both Financial Inclusion ($\beta = 0.42$, $p = 0.000$) and Service Offered ($\beta = 0.27$, $p = 0.000$) significantly and positively influence Trust (T). The stronger effect of FI suggests that ease of digital savings, access to financial products, and participation in the digital payment ecosystem substantially enhance users' confidence in neobanking platforms. Meanwhile, the service dimensions such as usability, accessibility, transaction reliability, and customer support also contribute meaningfully to trust, though to a slightly lesser extent.

The very high loading of Trust (0.98) on its items indicates that trust among users is primarily shaped by perceptions of security, reliability, and consistency in digital financial operations. This aligns with the structural findings, where both FI and SO significantly drive trust outcomes.

Hypothesis H1: Financial Inclusion (FI) has a significant positive effect on Trust (T).
The SEM model shows a strong and statistically significant path from Financial Inclusion to Trust ($\beta = 0.42$, $t = 6.21$, $p = 0.000$). This indicates that as users experience greater access to digital financial products, higher frequency of digital transactions, and improved ability to save or invest online, their trust in neobanking services substantially increases.
The factor loadings for FI indicators (0.80–0.92) demonstrate excellent reliability, and the AVE (0.843) confirms substantial convergent validity. The effect size ($f^2 = 0.14$) indicates a moderate practical impact on Trust, while the predictive relevance ($Q^2 = 0.12$) confirms the model's capability to predict trust outcomes.
Thus, H1 is supported as Financial Inclusion emerges as a major driver of trust in digital financial platforms.
Hypothesis H2: Services Offered (SO) have a significant positive effect on Trust (T).
The structural path from Service Offered to Trust is positive and highly significant ($\beta = 0.27$, $t = 4.89$, $p = 0.000$). This confirms that users' trust increases when neobanks provide easy-to-use interfaces, multiple financial services, accessible mobile applications, reliable transactions, and responsive customer support.
High factor loadings for SO items (0.86–0.90) and high AVE (0.893) indicate a strong and valid measurement model. The effect size ($f^2 = 0.08$) reflects a small-to-moderate influence, meaning service quality matters significantly, though less strongly than financial inclusion. Predictive relevance ($Q^2 = 0.12$) confirms the model's capacity to accurately forecast trust based on perceived service quality. Accordingly, H2 is fully supported as Service Offered meaningfully enhances customer trust in neobanking platforms.

V. CONCLUSION

In conclusion, AI based neo-banking emerges as a significant driver of financial inclusion , blending convenience, literacy, and behavioral improvement. The research findings indicate a strong positive relationship between trust and financial inclusion indicating positive impact of financial inclusion on trust and also a strong positive impact of services offered by neobanks on financial inclusion . However, the findings highlight certain challenges, including data security concerns, cybersecurity risks, and the need for regulatory oversight. Addressing these issues is critical to sustaining trust and maximizing the empowering potential of neo-banking. By reducing traditional barriers associated with physical branches and complex banking procedures, neo-banking enables access for young adults, first time users, gig workers, and underserved populations, thereby broadening the reach of formal financial systems. Policymakers, financial institutions, and technology innovators can leverage these insights to design secure, inclusive, and user-centric digital banking solutions that further strengthen financial autonomy and economic participation.

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