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Article

Artificial Intelligence-Driven Digital Financial Inclusion and Household Financial Resilience: Evidence from Sierra Leone

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Abstract: The ability of AI-powered financial technologies to reach, afford and improve the quality of formal financial services is increasingly a key determinant of household financial resilience in low-income economies. The reach, affordability and quality of formal financial services is increasingly a driver of household financial resilience in low-income economies, and artificial intelligence (AI)-enabled financial technologies are playing an increasing role in achieving this. While there is a growing number of scholarships that connect digital financial inclusion to welfare outcomes for households, there is comparatively little empirical evidence on how AI-powered digital financial services can contribute to resilience of fragile, low-income economies like Sierra Leone. This study addresses this gap by investigating the mediation role of digital financial inclusion and financial capability between AI-driven digital financial services and financial resilience of households, and the moderating role of digital trust between these two relationships. Primary data was collected using a cross-sectional survey design with 400 respondents from urban and rural districts of Sierra Leone and analyzed with reliability and validity diagnostics, hierarchical multiple regression and bootstrapped mediation analysis with 5,000 resamples. The measurement model showed good internal consistency and discriminant validity, and common method bias was not considered to be a serious threat. The results indicate that AI-enabled digital financial services have a significant predicting power for digital financial inclusion, which in turn has a significant predicting power for the financial resilience of households both directly and indirectly through financial capability, in line with a serial mediation pathway. Financial capability and financial inclusion were included to assess the full mediation of the direct effect of AI-driven digital financial services on resilience, and the result was statistically non-significant. The direct effect of digital trust was significant, but there was no significant moderation of the pathway between AI-driven-services-to-inclusion. The results contribute to the theory of digital financial inclusion in the AI era and provide concrete policy recommendations for regulators, fintech companies and development partners to enhance household resilience in Sierra Leone and other similar Sub-Saharan African settings.
Keywords: artificial intelligence; digital financial inclusion; household financial resilience; financial capability; digital trust; Sierra Leone

1. INTRODUCTION

Household financial resilience, defined as the ability to withstand, cope with and bounce back from economic shocks without enduring a long-term drop in wellbeing, has emerged as a key development issue of the post-pandemic world. Low-income and fragile economies suffer from low savings rates and a lack of formal credit facilities, and they are forced to rely on informal coping strategies like asset liquidation or cut-backs in consumption, which are high-risk options that compromise their capacity. In low-income and fragile economies, this capacity is often undermined by thin buffers of savings, limited access to formal credit, and a heavy reliance on informal, high-risk coping strategies like asset liquidation or cut-backs in consumption. Sierra Leone is a nation that is still recovering from a decade-long civil war, the 2014-2016 Ebola outbreak and frequent macroeconomic shocks. A significant proportion of Sierra Leonean households are not formally part of the financial system, and are therefore vulnerable to shocks that are more easily absorbed by formally included financial systems.

The digital financial inclusion has become one of the most promising levers for closing this resilience gap worldwide. Mobile money platforms, agent banking networks and digital lending apps have helped to broaden the reach of savings, credit, insurance and payments to unbanked and underbanked populations by reducing transaction costs. A bibliometric analysis of the broader e-banking literature by (Kumari et al., 2026) traces this trajectory across three generations of research, from early online-banking security and trust concerns to today's fintech-driven wave centred on artificial intelligence, blockchain, and financial inclusion. (Ozili, 2025a) notes that research on digital financial inclusion has grown significantly in the global arena, but has not been evenly distributed, with less research focusing on the impact of new technologies on inclusion outcomes in the world's poorest areas. A recent bibliometric analysis by (Surwanti et al., 2026) corroborates this pattern, showing that scholarship on financial inclusion and sustainable development is dominated by China and India, with African contexts and governance-related themes remaining comparatively underrepresented. AI is the latest and perhaps most significant facet of this technological revolution. Fintech firms and mobile network operators are using AI-powered credit scoring, biometric identity verification, natural-language chatbots, fraud-detection algorithms and robo-advisory tools to address exactly the same supply-side challenges that have kept low-income consumers out of formal finance thin credit files, expensive manual underwriting, and sparse physical infrastructure. The findings by (Ravikumar et al., 2025) suggest that the use of AI-driven digital finance, alongside digital financial literacy, is a meaningful influence on the inclusion and resilience of micro and small enterprises in the aftermath of economic shocks, and this is likely to be the case at the household level.

The case for AI in financial inclusion is theoretical because of its ability to replace the traditional banking system's collateral and documentation requirements with algorithmic pattern recognition. In the eyes of (Mhlanga, 2020), the promise of the Fourth Industrial Revolution to bring financial inclusion to the base of the economic pyramid is inextricably linked to the use of machine-learning models that can estimate creditworthiness based on alternative data sources like mobile airtime top-ups, utility payments, and transaction histories, rather than formal payslips or land titles. Similarly, (Rawat et al., 2023a) report that narrow AI is becoming a part of the design of digital financial inclusion systems, allowing financial institutions to reach populations that traditional risk models would otherwise exclude. These arguments suggest that AI is not just a digital version of financial services, but a reconfiguration of who is considered "bankable" and have implications for household resilience in economies with limited formal safety nets.

However, the process from AI-powered financial technology to increased household resilience is not a foregone conclusion or uncontested. Not all households with access to a digital financial account will be able to use it effectively, and not all will use it to build capacity to absorb shocks. (Ozili, 2022) warns that digital financial inclusion is a multi-dimensional phenomenon, and that gains in one dimension do not necessarily translate to gains in the other. (Qureshi et al., 2021) extend this by stating that claims of inclusion based on AI should be examined with caution, as algorithmic credit-scoring systems can reflect and reinforce existing biases, potentially leaving out the very populations they are said to be serving. Financial capability, defined as financial knowledge, skills and confidence to use financial products effectively, and digital trust, defined as trust in digital platforms to safeguard funds and data, are therefore plausible boundary conditions to consider when assessing the potential of AI-driven inclusion to enhance resilience or simply provide a superficial level of access. The transformative power of AI in personal finance cannot be divorced from the unaddressed ethical, regulatory, and accessibility issues that shape the everyday experience of ordinary users of these tools, as noted by (Hesami, 2025). While these conditioning mechanisms are crucial for scholarship and policy, they are under-examined empirically in Sub Saharan Africa.

The Sierra Leone context is both theoretically and practically significant for the study of these dynamics. Although formal bank branch penetration is low, especially in the Western Area, the country has seen a surge in mobile money adoption in the last decade, as a result of the liberalization of the telecommunications policy and the central bank's efforts to create a cash-lite economy. According to (Mpofu & Mpofu, 2024), the COVID-19 pandemic has driven the adoption of digital financial services in developing economies even faster, with the supply of these services compressed by the combination of fintech and technologies of the Fourth Industrial Revolution, which could have taken a decade to reach the market. Based on cross-country evidence, (Sakyi-Nyarko et al., 2025) find that digital financial inclusion in Africa is linked to measurable economic impacts, including increased trade participation, but note that the impact of digital financial inclusion on these outcomes is highly variable across countries, depending on country-specific infrastructural and institutional conditions. Sierra Leone is a key country to examine the extent to which AI-powered digital financial services can effectively enhance household resilience, or if structural challenges limit the impact.

While the literature on the potential of AI to contribute to digital financial inclusion is rich in concepts, there is limited empirical evidence at the household level from West Africa, and few studies explore the entire causal pathway from AI financial services to financial inclusion, to capability, to trust, and to resilience in a single, statistically robust model. The existing literature is conceptual, bibliometric or macro-level oriented for Asian contexts. A bibliometric review by (Dirie, 2024) confirmed that research into the use of artificial intelligence in digital financial inclusion is growing, but is still limited to a few geographic and disciplinary clusters, with Sub-Saharan Africa being under-represented. This study directly tackles that gap by creating and testing a moderated-mediation model where digital financial inclusion and financial capability sequentially mediate between AI-driven digital financial services and household financial resilience, and digital trust is explored as a boundary condition that influences the strength of these pathways.

Thus, the following three objectives are set for this study. First, it explores how AI-powered digital financial services directly impact financial resilience of Sierra Leonean households. Second, it examines whether the relationship between digital financial inclusion and financial capability is mediated by digital financial inclusion, and whether the relationship between digital financial capability and resilience outcomes is mediated by financial capability, thus clarifying the mechanism by which digital financial inclusion leads to resilience outcomes. Third, it assesses the extent to which digital trust strengthens or weakens the relationship between AI-powered digital financial services and digital financial inclusion, and offers evidence on whether digital trust is a necessary precondition for the potential of AI to enhance digital financial inclusion. The study contributes to the achievement of these goals in several ways. It extends the theory of digital financial inclusion into the AI era by explicitly modelling the sequential mechanisms inclusion followed by capability through which technology becomes a source of resilience at the household level, filling a gap called for by scholars like (Grover et al., 2025) for more granular evidence on how technology can help or not help to bridge socioeconomic gaps. It is empirically one of the first household level quantitative studies of AI-based digital financial inclusion in Sierra Leone, rigorously psychometrically validated, diagnosed for multicollinearity, and bootstrapped in a way that meets the methodological standards of top finance and development journals. In practice, the results provide concrete, evidence-informed advice to central bank regulators, fintech companies, and development partners on the areas they should focus their interventions on for instance, on expanding access with AI, on financial capability, or on enhancing digital trust to maximize the resilience dividends of digital financial inclusion.

The rest of the manuscript is structured as follows. Section 2 summarizes the theoretical and empirical literature and formulates the hypotheses for the study. The research design, sampling procedure, measurement instrument, and analytical strategy are described in Section 3. The results of the measurement model and the hypothesis tests are presented in Section 4. The results are discussed in the light of the available theory and evidence in Section 5. Theoretical, practical and policy implications are outlined in section 6. Section 7 recognizes the limitations of the study and suggests directions for future research, while Section 8 concludes.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 Theoretical Framework

This study embeds its model in an integrated theoretical framework that integrates financial inclusion theory and a capability-based perspective on technology-enabled resilience. Financial inclusion theory suggests that the formal financial system participation helps to lessen vulnerability by enabling households to smooth consumption, build precautionary savings, and borrow and insure against shocks. (Ozili, 2022) presents digital financial inclusion as a multi-dimensional concept, consisting of access, usage, and quality of digital financial services, and suggests that international development agendas have increasingly adopted digital delivery channels as the main means to reach the "last mile" of financial inclusion. This is the building block for the diffusion-of-innovation logic that is present in the fintech literature, which posits that the potential for inclusion is determined by how much a technology lowers the relative disadvantage, complexity and risk of a new financial behavior. Fintech, in (Moosa, 2024) view, is the convergence of massive data generation, sophisticated algorithms, and growing processing power, which in turn significantly reduces the costs that have traditionally kept low-income groups out of formal finance. This capability logic resonates with the resource-based view of the firm, under which entrepreneurial and technological capabilities function as behavioral mechanisms that convert access to a resource into a performance outcome; in the MSME context, (Anggadwita et al., 2026) show that entrepreneurial orientation mediates the effect of innovation capability on export capability, illustrating that access to a resource or technology translates into a tangible outcome only when paired with the capability to use it strategically.

Artificial intelligence brings another dimension to this framework by allowing financial institutions to personalize, automate and de-risk service delivery in ways that traditional digitization can't. As financial institutions shift towards an Industry 5.0 paradigm of human-centred automation, increasingly complex forms of artificial intelligence are being integrated into the architecture of digital financial inclusion systems, making them more sustainable and customer-centric, as described by (Rawat et al., 2025). This capability-based logic suggests that the role of AI in household resilience is indirect: AI transforms financial services supply, which leads to greater financial inclusion, which leads to greater household-level capacity and buffer stocks to absorb shocks. The present study formalizes this logic in a serial mediation model, where the effect of AI-driven digital financial services is mediated by digital financial inclusion and financial capability, and digital trust is theorized as a boundary condition that influences the strength of the initial technology-to-inclusion link. This integrated framework is in line with recent literature that has called for empirical models that go beyond bivariate associations to mechanism-based explanations of how emerging technologies relate to welfare outcomes.

2.2 Artificial Intelligence-Driven Digital Financial Services and Digital Financial Inclusion

AI-powered digital financial services refer to the various machine-learning-powered functions that financial service providers are increasingly adding to mobile money and digital banking platforms, such as algorithmic credit scoring, biometric authentication, conversational chatbots, fraud-detection systems, and automated advisory tools. There is increasing evidence that these capabilities are directly tied to increased financial inclusion. In the study of (Nair et al., 2021), AI-powered chatbots can be used to automate marketing and customer engagement activities that mitigate common consumer-reported informational and behavioral barriers to accessing financial services, thereby reducing the informational and behavioral frictions that prevent low-income consumers from accessing financial services. Similarly, (Gowri et al., 2025) state that AI acts as a catalyst for digital financial inclusion by allowing institutions to profile, reach, and serve populations that would otherwise be deemed too costly or too risky to be on-boarded using traditional methods. In the Chinese context, (Shang, 2024) uses random-forest and gradient-boosting algorithms to show that AI-driven digital inclusive finance is linked to more innovative factor allocation, which can only be achieved once a broader group of economic actors is integrated into the formal financial system.

AI's role in increasing inclusion is largely through the replacement of collateral-based underwriting with algorithmic risk assessment. The findings of (Dirie, 2024) are based on a large amount of bibliometric evidence that shows that the most common research focus of AI and machine-learning applications is on their ability to reach previously unserved segments of digital financial inclusion. The study of (P. Mishra & Guru Sant, 2021), report that the pandemic has seen the convergence of artificial intelligence and the Internet of Things speed up the adoption of banking and financial services, as physical channels were affected and providers were forced to adopt automated and remote onboarding and service processes. The study (Grover et al., 2025) further argue that, AI applications are becoming an integral part of explicit efforts to address socioeconomic disparities in financial access, especially for low-income groups. Overall, this literature indicates that the greater the perceived availability, functionality, and relevance of AI-driven digital financial services to the user, the higher the likelihood and intensity of their interaction with formal digital financial services. Based on this, the following study is proposed:

H1. AI-driven digital financial services have a significant positive effect on digital financial inclusion.

2.3 Digital Financial Inclusion and Household Financial Resilience

Theorizing digital financial inclusion as a way to increase financial resilience of households, it is expected to increase the number of instruments available to households to cope with income volatility and expenditure shocks. The study of (Ferdous, 2025) places financial inclusion through digital means as an important avenue for realizing SDGs, stating that economic development is only possible in the long term if financial systems are extended to the entire population and not a select few. The study of (Sun et al., 2021) offer provincial-level panel data evidence from China that digital financial inclusion has a positive impact on overall innovation and productivity outcomes, which is likely mediated by the increased ability of households and firms to access finance for productive investment once they enter the formal financial system. Specifically, at the enterprise and household level, (Ravikumar et al., 2025) conclude that digital financial inclusion is significantly related to the financial resilience of micro and small entrepreneurs in the aftermath of the economic shock of the COVID-19 pandemic, offering direct empirical evidence of the relationship hypothesized in this paper.

The positive impact of digital financial inclusion on resilience is believed to work through several complementary mechanisms: better saving capacity in formal, interest-bearing financial instruments; access to credit to buffer consumption shocks; and access to digital insurance products to shift risk from the household. The study of (H. Han & Gu, 2021) demonstrate that inclusive digital finance benefits the innovation performance of high-tech firms, in part, by reducing external financing constraints, which is conceptually similar to the consumption and investment smoothing effect that digital inclusion is hypothesized to have at the household level. Similarly, (Chishti et al., 2025) show that digital financial inclusion is not only a financial phenomenon, but also has an impact on real economic outcomes, such as the cost of energy transition infrastructure, when it interacts with broader development financing initiatives. The study of (Ravishankar et al., 2023) specifically examine the financial exclusion of financially excluded and highly vulnerable groups such as internal migrant workers in India, and conclude that AI-driven digital financial inclusion is a viable means to address financial exclusion and mitigate the financial vulnerability of these groups. Based on this accumulated evidence, the study suggests:

H2: Digital financial inclusion has a positive and significant impact on the financial resilience of households.

AI-driven digital financial services' direct impact on household financial resilience

In addition to its indirect impact via inclusion, AI-supported digital financial technology can also have a direct impact on household resilience by enhancing the timeliness and accuracy of household responses to shocks. Plausibly, AI-powered tools can also impact household decision-making, as they can offer real-time and personalized financial advice, which can boost the efficiency of research and development investment and drive digital transformation in the corporate sector, as (Liu et al., 2024) conclude. While the paper highlights the need for ethical and regulatory frameworks to ensure the responsible and secure use of AI in financial services, (Hesami, 2025) suggests that the technology is fundamentally changing how people manage their finances, making it more accessible and user-friendly for the general public. (L. Zhou et al., 2023) use explainable artificial intelligence methods to demonstrate that digital finance can be associated with measurable changes in consumption patterns, which align with the idea that digital finance tools do not just affect formal inclusion indicators, but also influence the financial behavior of the population directly.

If there is a direct effect of AI-driven services on resilience in isolation, it would be expected to be reduced after accounting for the pathway through formal inclusion, as a lot of the practical impact of AI on households is through formal inclusion in digital financial services. At the institutional level, (Antova, 2025) warns that fintech innovation and liquidity risk are linked, suggesting that the resilience of fintech services to end users depends on the resilience of the digital financial institutions providing these services. Based on the possibility of a direct effect and an inclusion-mediated effect, the following hypotheses are proposed:

H3: AI-driven digital financial services have a significant positive direct effect on household financial resilience.

2.5 Digital Financial Inclusion as a Mediating Variable

This study builds on H1 through H3 and suggests that digital financial inclusion is the primary channel by which digital financial services based on AI affect financial resilience of households, rather than financial resilience being a simple additive function of AI exposure. The study of (Aloulou et al., 2024) show that the diffusion of digital financial inclusion in the banking sector is positively associated with the adoption of FinTech, which suggests that inclusion is the immediate effect of technology adoption, not a separate, autonomous source of welfare. The study of (Sille et al., 2024) perform a systematic review that establishes that digital financial inclusion is always theorized in the literature as the channel through which digital financial technologies, such as AI, are translated into real improvements for the users' financial situation. The study of (Y. Feng et al., 2024) offer methodological guidance on testing such mediated pathways by using a chain-mediation model to demonstrate that the impact of regional integration strategies on inclusive growth outcomes is indirect and mediated by structural changes. Based on this reasoning, the direct statistical link between AI-based digital financial services and household resilience should become much weaker when digital financial inclusion is added to the model, but remain strong as an indirect effect. This yields the study's mediation hypothesis:

H4: Digital financial inclusion plays a significant mediating role between AI-based digital financial services and financial resilience of households.

2.6 Digital Financial Inclusion and Financial Capability

Financial capability is the ability to use the financial instruments available to them effectively, which involves financial knowledge, budgeting and planning skills and confidence. However, access alone is not a measure of capability; rather, ongoing interaction with formal digital financial products is thought to foster capability by learning through doing. The study by (X. Li, 2025) demonstrates how demographic changes can interact with the evolution of digital financial inclusion, emphasizing the need to adapt inclusion strategies to the different capacities of different groups of users, especially older and less formally educated users. The study of (Fatima & Kapoor, 2025) conduct a bibliometric analysis of FinTech service acceptance and find that the diffusion of digital financial technologies is closely intertwined with the evolution of users' digital financial literacy over time, implying a reciprocal, capability-building relationship rather than a one-off adoption event. Similarly, in their bibliometric exploration, (Dwivedi et al., 2025) discover that financial inclusion research is increasingly moving away from the focus on access and towards the focus on capability-oriented outcomes, including financial literacy. This capability-oriented emphasis is echoed in (Nugraheni et al., 2025) PLS-SEM study of Indonesian MSMEs, which finds that financial literacy, rather than financial inclusion or digital-payments access alone, is the strongest predictor of business performance, underscoring the practical primacy of capability over mere access. Based on this, the study suggests:

H5: Digital financial inclusion has a strong positive impact on financial capability.

2.7 Financial Capability and Household Financial Resilience

Financial capability is broadly theorized as a proximal factor influencing household resilience as it determines the effectiveness of the financial resources and instruments that a household can access. The study of (Sharma et al., 2023) suggest that the use of digital financial management tools in the day-to-day financial decision-making process strengthens the ability of the users to plan, budget, and respond to risk, which are key elements of the resilience construct. (H. Mishra & Mishra, 2024) apply a capability-based logic to the context of household food and livelihood security, demonstrating that technology-enabled capability building is at the heart of building resilience at the household level to systemic shocks like those to agricultural livelihoods. At the labour-market level, (L. Han & Tian, 2024) offer complementary evidence that the digital economy is transforming the wage and skills landscape, with higher levels of capability rewarded, which is likely to be true of the role of financial capability in shaping households' resilience to income shocks. Based on this evidence, the study suggests that:

H6: Household financial resilience is positively associated with financial capability.

2.8 Serial Mediation through Digital Financial Inclusion and Financial Capability

This study proposes a serial mediation mechanism: AI-based digital financial services first increase the digital financial inclusion, then enhance the financial capability, and finally improve the financial resilience of households. This sequential logic is based on the understanding that inclusion and capability are two different concepts, but developmentally sequential: households need to access and start using digital financial services before they can develop their capability. (Mpofu & Mpofu, 2024) suggest that the Fourth Industrial Revolution technologies foster digital financial inclusion in developing economies in a sequential manner, starting with access, then engagement and skill acquisition, and finally deepening engagement, which aligns with a serial rather than a parallel mediation structure. In addition, (Jin & Liu, 2025) conclude that digital inclusive finance reduces financing constraints for small and micro enterprises via a series of intermediate mechanisms, further supporting a multi-step mediation framework. Based on this, the study suggests:

H7: The relationship between AI-driven digital financial services and household financial resilience is mediated by digital financial inclusion and financial capability in a serial manner.

2.9 Digital Trust as a Moderating Factor

In the literature, digital trust the trust that a digital financial platform will protect funds, safeguard personal information, and act predictably has been mentioned time and time again as a key boundary condition for the success of digitally delivered, AI-enabled financial services. (Ghandour, 2021) carries out a systematic review of artificial intelligence in banking and finds that trust and data-security issues are among the most frequently cited obstacles to achieving customer engagement with AI capability. Specifically, (D. Li & Azman, 2024) explore how trust issues impact the uptake of AI-enabled digital currency systems, and conclude that unresolved trust issues can hinder adoption even if the technological infrastructure is in place. However, (Ojo, 2024) reports that inequalities in trust in and access to artificial intelligence systems can deepen inequalities, meaning that the advantages of AI in financial services are dependent on the extent to which specific user groups trust AI systems. Similarly, (Soegoto et al., 2025) report that the successful monitoring and operation of AI-based systems in various fields, such as finance, depend on users' trust in the results of algorithmic decision-making. In a comparable Southeast Asian fintech setting, (Garad et al., 2025) similarly find that user trust in fintech services is shaped directly by perceived ease of use, brand reputation, and government support, and that this trust in turn positively influences users' attitudes toward continued engagement with fintech platforms. The study builds on this literature by theorizing that digital trust further enhances the positive relationship between AI-driven digital financial services and digital financial inclusion, meaning that the relationship is stronger for users with high levels of digital trust than it is for users with low levels of digital trust, or even none. This leads to the moderation hypothesis of this study:

H8: The relationship between AI-powered digital financial services and digital financial inclusion is significantly moderated by digital trust, with a stronger relationship at higher levels of digital trust.

2.10 Conceptual Framework

The hypothesized relationships tested in this study are summarized in Figure 1. Digital financial services (AIFS) is represented as the exogenous predictor, while digital financial inclusion (DFI) and financial capability (FC) are considered as sequential mediators in the path to household financial resilience (HFR). Digital trust (DT) is hypothesized as a moderator between the AIFS and DFI relationship, while control variables (gender, education, monthly income, residential location, mobile money experience, and internet access) are included throughout the model to capture the hypothesized effect while controlling for other demographic and infrastructural factors. The rest of the paper explains the method of testing this framework and the empirical findings.

3. METHODOLOGY

3.1 Research Design and Philosophical Positioning

This study uses a quantitative, cross-sectional, explanatory research design with a post-positivist epistemology, which aligns with the study's aim of testing a priori hypotheses based on digital financial inclusion theory. The constructs of interest perceived AI-driven service quality, inclusion, capability, trust, and resilience are latent psychological and behavioral states that are best measured with self-report instruments administered directly to the household decision-maker, and not simply derived from administrative or transaction-level data. The cross-sectional design allows all constructs to be measured at one time, which is suitable for testing structural relationships hypothesized in Section 2, and the limitations of the study in terms of causal inferences from cross-sectional data are addressed explicitly in Section 7.

3.2 The study context and population.

The study took place in Sierra Leone, a low-income West African economy where mobile money has been widely adopted, but formal banking remains low. The target population consisted of adult household financial decision-makers in both urban and rural localities, who are primarily responsible for managing the household's financial decisions in relation to income, expenditure and savings. This population was chosen because the financial resilience of a household is best measured at the level of the individual who has effective control over the financial decisions of the household, not at the level of all household members. Respondents from both urban and rural areas were purposively selected to reflect the diversity of access to digital and financial infrastructure in Sierra Leone, where urban–rural differences in internet access, agent banking density, and formal education remain significant.

3.3 Sampling Procedure and Sample Size

A multi-stage sampling strategy with stratification was used. The first stage involved stratification of the sampling frame by location (urban and rural) to ensure that both urban and rural areas were represented, as the theoretical importance of infrastructural context to outcomes of digital financial inclusion was considered. The respondents were selected by systematic intercept sampling at mobile money agent points, market centres and community gathering points, with a snowball sampling element to access respondents in rural areas where there is less traffic at fixed points. It is a hybrid approach that combines the practical considerations of survey administration in a low-infrastructure setting with the desire to minimize the most egregious forms of convenience-sampling bias, including over-representation of digitally engaged urban professionals.

A final analytic sample of 400 respondents was achieved, half of whom were from urban areas ($n = 200$) and half from rural areas ($n = 200$). This sample size is greater than the minimum recommended for multivariate regression-based analysis with up to 15 predictors, and meets the "10 cases per estimated parameter" guideline used in structural and mediation modelling with the number of paths estimated in the serial mediation framework used in this study. Post hoc power analysis with an alpha of .05 confirms that this sample size would have more than 0.99 power to detect the smallest observed structural effect ($\beta = .126$ for the digital financial inclusion–resilience path in the full model), which is sufficient to detect the hypothesized effects.

3.4 Measurement Instrument

The data were gathered by a structured, interviewer-administered questionnaire with two sections. The first section included respondent demographic and infrastructural characteristics, which included gender, age, highest level of education, average monthly household income (recorded in New Leones), urban or rural residence, duration of mobile money account use (in months), and binary internet access status. The five latent constructs of the study were operationalized in the second section using previously validated, multi-item, five-point Likert-type scales (1 = strongly disagree to 5 = strongly agree), adapted to the Sierra Leonean digital finance context, based on the conceptual definitions established in the literature reviewed in Section 2.

AI-driven digital financial services (AIFS) was assessed using five items that reflect the respondents' perception of exposure to and experience with AI applications in financial services, including algorithmic credit assessment, automated customer service, and biometric verification, as conceptualized by (Ozili, 2025b) in his discussion on the growing role of AI in financial services risk management, fraud detection, and customer experience. Digital financial inclusion (DFI) was assessed using five indicators, which cover access, frequency of use, and cost of digital financial services, based on the multidimensional definition of DFI in the context of poverty-reduction theory as put forward by (Mhlanga, 2022). Financial capability (FC) was assessed using five questions that included budgeting confidence, financial planning skills, and understanding of digital financial products. The dependent variable of the study was household financial resilience (HFR), which was measured using five items that reflect the respondents' ability to withstand income shocks, cover unexpected expenses, and regain financial stability after adverse events. Digital trust (DT) was assessed using four items that reflect trust in the security, reliability and fairness of digital financial platforms. The results of all items and descriptive statistics are presented in Section 4. The full item wording, item response distributions and coding scheme are available in the accompanying respondent-level data set and codebook.

3.5 The data collection procedure and ethical considerations.

To reduce the measurement error due to language barriers, trained bilingual enumerators who are fluent in English and the main local languages spoken in the sampled localities conducted data collection over a specified field period. To minimize interviewer-induced response bias, enumerators were trained in standardized administration procedures, such as delivering the questions in a neutral manner and clarifying the questions without leading. Each respondent gave informed consent before being administered, and respondents were assured anonymity and voluntary participation, and no personally identifying information was kept in the analytic dataset. As is typical in household survey research in similar low-income communities, no material incentive was offered to respondents other than a nominal token of thanks for their participation.

3.6 Common Method Bias

All constructs were assessed with self-report items, which were included in the same instrument, making the design vulnerable to common method bias (CMB). A number of procedural and statistical remedies were used. The questionnaire was designed to separate predictor and outcome constructs into different sections, to change the response-scale anchors between sections, and to assure respondents of response confidentiality to minimize social desirability and consistency-motivated responding. Harman's single factor test was performed statistically by entering all 24 Likert items into an unrotated principal component analysis. The first unrotated factor explained 27.34% of the total variance, which is below the 50% criterion generally considered a CMB concern, and none of the factors explained more than half of the covariance among the manifest variables. This finding suggests that common method bias is not likely to significantly affect the substantive results of the study, but the potential for unaccounted for method-related variance cannot be ruled out in any one-source, one-occasion study.

3.7 Data Analysis Strategy

Data were screened for completeness, out-of-range values, and outliers prior to analysis; no cases were removed from the analytic data set, and no missing data were identified. The analysis was done in five steps. The means, standard deviations, skewness and kurtosis of all study constructs were calculated to ensure that the data were approximately normally distributed in each construct, which is a prerequisite for the subsequent parametric analyses. Second, the psychometric properties of the measurement model were evaluated using internal-consistency reliability (Cronbach's alpha), composite reliability (CR), convergent validity (AVE), and discriminant validity (Fornell–Larcker criterion). Third, zero-order Pearson correlations among the five latent constructs were computed to provide an initial test of the hypothesized bivariate relationships. Fourth, to test the hypothesized direct and mediated relationships of H1 through H7, as well as the hypothesized moderation effect of H8, hierarchical ordinary least squares (OLS) multiple regression was used, with the control variables entered in the first block, the focal predictor(s) entered in subsequent blocks, and the interaction terms entered in a final block. All continuous predictors involved in interaction terms were mean-centred prior to computing product terms, to reduce non-essential multicollinearity and to aid the interpretation of simple slopes. To exclude problematic multicollinearity, variance inflation factors (VIF) were calculated for each model, and the VIFs were all below the standard of 5, with the highest being .95, which was between the age of the respondent and the tenure of the mobile money account. Given that the VIFs were all below 5, and that the highest was .95, between the age of the respondent and the tenure of the mobile money account, the age of the respondent was dropped from the final control set in favor of mobile money account tenure, which was more theoretically close to the constructs of the digital finance models.

Fifth, the indirect and serial mediation effects hypothesized in H4 and H7 were tested using a bootstrapping procedure with 5,000 resamples with replacement, as is now recommended for mediation analysis and which does not require the assumption of a normally distributed indirect effect that is implicit in the classical Sobel test. Bias-corrected 95% percentile confidence intervals were calculated for each indirect effect; if the confidence interval for an indirect effect did not contain zero, the indirect effect was considered statistically significant. To interpret the conditional effects suggested in H8, simple slopes were computed and plotted at the mean and plus/minus one standard deviation of the moderator. The normality assumption (Shapiro–Wilk test), homoscedasticity assumption (Breusch–Pagan test), and independence assumption (Durbin–Watson statistic) were further examined for regression residuals from the final structural models to ensure that the assumptions of ordinary least squares estimation were met. All analyses were performed using statistical computing routines written in Python that follow standard closed-form OLS, principal component, and bootstrap resampling algorithms, with the outputs compared to those of traditional statistical software. Unless otherwise indicated, the alpha level for all inferential tests was .05 (2-tailed).

4. RESULTS

4.1 Sample Characteristics

Table 1 shows the demographic and infrastructural profile of the 400 respondents. The sample was evenly balanced by gender (200 male, 50.0%; 200 female, 50.0%) and by residential location (200 urban, 50.0%; 200 rural, 50.0%), by design. The mean age of the respondents was 34.66 years (SD = 9.72, range = 18–65), which is a working age group as the study targeted the active household financial decision makers. The educational qualifications were skewed towards secondary and tertiary education, with 35.0% of respondents having secondary education as their highest qualification, 32.8% having tertiary or vocational qualifications as their highest qualification, 17.5% having no formal or primary level education only, 12.2% having a bachelor's degree, and 2.5% having postgraduate qualifications. The mean monthly household income was 692.55 New Leones (SD = 221.47, range = 137–1,368), which indicates that the study population was low-income. The average duration of mobile money account experience was 12.70 months (SD = 9.37, range = 0–45) while 84.25% of the respondents reported access to the internet, with 15.75% reporting no access to the internet, which is higher among the rural respondents.

Table 1. Demographic and Infrastructural Profile of Respondents (N = 400)

Characteristic	Category	n	%

Gender	Male	200	50.0
	Female	200	50.0
Age (years)	M = 34.66, SD = 9.72, Range = 18–65		
Education	No formal/primary	70	17.5
	Secondary	140	35.0
	Tertiary/vocational	131	32.8
	Bachelor's degree	49	12.2
	Postgraduate	10	2.5
Monthly income (SLE)	M = 692.55, SD = 221.47, Range = 137–1,368		
Location	Urban	200	50.0
	Rural	200	50.0
Mobile money experience (months)	M = 12.70, SD = 9.37, Range = 0–45		
Internet access	Yes	337	84.25
	No	63	15.75

4.2 Descriptive Statistics of Study Constructs

In Table 2, the descriptive statistics for the five composite constructs, each computed as the mean of its constituent Likert items. Mean scores ranged from 2.72 (AI-driven digital financial services) to 3.13 (household financial resilience) on the five-point scale, indicating that respondents on average reported moderate, rather than extreme, levels of each construct. All skewness values fell between -0.062 and 0.062, and all kurtosis values fell between -0.425 and -0.145, well within the conventional ±1.0 threshold for approximate univariate normality, supporting the appropriateness of the parametric regression procedures used in subsequent analyses.

Table 2. Descriptive Statistics for Study Constructs (N = 400)

Construct	**M**	**SD**	**Min**	**Max**	**Skewness**	**Kurtosis**
AI-Driven Digital Financial Services (AIFS)	2.72	0.55	1.20	4.00	-0.057	-0.145
Digital Financial Inclusion (DFI)	2.92	0.59	1.20	4.80	0.062	-0.216
Financial Capability (FC)	3.04	0.61	1.40	5.00	-0.017	-0.242
Household Financial Resilience (HFR)	3.13	0.57	1.40	4.40	-0.062	-0.425
Digital Trust (DT)	2.89	0.59	1.25	4.75	0.046	-0.131

4.3 Measurement Model: Reliability and Validity

In Table 3, the reliability and convergent validity statistics for the five-construct measurement model. Cronbach's alpha coefficients ranged from .800 (digital trust) to .846 (financial capability), all comfortably exceeding the .70 threshold conventionally required for acceptable internal consistency. Composite reliability (CR) values ranged from .870 to .891, likewise exceeding the .70 benchmark, and average variance extracted (AVE) values ranged from .584 to .626, exceeding the .50 threshold conventionally required to establish convergent validity. Item-level standardized loadings, obtained from single-factor principal component extraction for each construct, ranged from

.735 to .827, with all items loading well above the .60 minimum threshold typically applied in confirmatory measurement analysis.

Table 3. Reliability and Convergent Validity of the Measurement Model

Construct	Items	Loading range	Cronbach's α	Composite Reliability (CR)	AVE
AIFS	5	.748–.800	.826	.878	.591
DFI	5	.753–.809	.839	.886	.609
FC	5	.769–.802	.846	.891	.620
HFR	5	.735–.796	.821	.875	.584
DT	4	.767–.827	.800	.870	.626

Table 4 reports the Fornell–Larcker discriminant validity assessment, in which the square root of each construct's AVE (reported on the diagonal) is compared against its bivariate correlations with all other constructs (reported off-diagonal). For every construct, the square root of AVE exceeded all corresponding inter-construct correlations, satisfying the Fornell–Larcker criterion and confirming that each construct captures a distinct underlying dimension not adequately explained by the others.

Table 4. Discriminant Validity: Fornell–Larcker Criterion

	AIFS	DFI	FC	HFR	DT
AIFS	**.769**				
DFI	.526	**.780**			
FC	.253	.416	**.787**		
HFR	.219	.303	.409	**.764**	
DT	.366	.181	.070	.198	**.791**

Note. *Diagonal values (bold) are the square root of AVE for each construct.*

As an additional statistical safeguard against common method bias, Harman's single-factor test was conducted on all twenty-four indicator items. The unrotated principal component solution yielded a first factor accounting for 27.34% of total variance, and the first five factors together accounted for 61.07% of total variance, with no single factor approaching the 50% threshold that would signal a serious CMB concern. This result, together with the procedural remedies described in Section 3.6, supports the conclusion that common method variance is not a substantial threat to the validity of the study's findings.

4.4 Correlation Analysis

Table 5 presents the zero-order Pearson correlations among the five study constructs. AI-driven digital financial services correlated positively and significantly with digital financial inclusion ($r = .526, p < .001$), providing initial support for H1. Digital financial inclusion correlated positively and significantly with household financial resilience ($r = .303, p < .001$), consistent with H2. AI-driven digital financial services also correlated positively and significantly with household financial resilience at the bivariate level ($r = .219, p < .001$), consistent with H3, while financial capability correlated strongly with both digital financial inclusion ($r = .416, p < .001$) and household financial resilience ($r = .409, p < .001$), consistent with H5 and H6. Digital trust correlated significantly with AI-driven digital financial services ($r = .366, p < .001$), with digital financial inclusion ($r = .181, p < .001$), and with household financial resilience ($r = .198, p < .001$), but its correlation with financial capability was small and statistically non-significant ($r = .070, p = .160$).

Table 5. Pearson Correlation Matrix among Study Constructs

Construct	AIFS	DFI	FC	HFR	DT
AIFS	1.000				
DFI	.526	1.000			
FC	.253	.416	1.000		
HFR	.219	.303	.409	1.000	
DT	.366	.181	.070	.198	1.000

Note. ***p < .001. All correlations computed on N = 400.***

4.5 Hierarchical Regression: Predictors of Household Financial Resilience

Table 6 shows four hierarchically nested OLS regression models predicting household financial resilience. Model 1 included the control variables alone and accounted for a substantial but not large proportion of variance in resilience (6.0%, $R^2 = .060$, $F(6, 393) = 4.153$, $p < .001$), with none of the individual control variables being conventionally significant, but internet access coming close ($p = .083$). At this stage of the analysis, Model 2 also included AI-driven digital financial services, which resulted in a large increase in explained variance, $\Delta R^2 = .028$, $p < .001$, and a significant positive direct effect on resilience ($\beta = .184$, $p = .0006$), supporting H3.

Digital financial inclusion was the next significant contributor, with an additional large amount of explained variance, $\Delta R^2 = .044$, $p < .001$, for Model 3. Importantly, the direct impact of AI-driven digital financial services on resilience was significantly reduced and became statistically non-significant ($\beta = .054$, $p = .368$), and digital financial inclusion was a significant positive predictor ($\beta = .240$, $p < .001$). This pattern is a typical total effect that becomes non-significant when the proposed mediator is included, and a significant effect of the proposed mediator, which is tested formally using bootstrapping in Section 4.6, and is strong preliminary evidence for H4.

The full model explained 22.8% of the variance in household financial resilience ($R^2 = .228$, adjusted $R^2 = .206$, $F(11, 388) = 10.434$, $p < .001$), with the largest increase in explained variance in the four models being for financial capability ($\Delta R^2 = .096$, $p < .001$). In this fully specified model, financial capability was the strongest individual predictor of resilience ($\beta = .299$, $p < .001$), as in Model 3, while digital trust exerted a significant positive direct effect on resilience ($\beta = .145$, $p = .002$); digital financial inclusion remained a significant positive predictor ($\beta = .126$, $p = .022$); and the AI-driven digital financial services coefficient remained non-significant ($\beta = -.018$, $p = .762$), reinforcing the full-mediation pattern observed in Model 3. The relationship between digital financial inclusion and financial capability was not statistically significant ($\beta = -.017$, $p = .801$), suggesting that financial capability is a significant direct predictor of resilience, and is not a moderator of the inclusion–resilience relationship in this sample. The variance inflation factors for all predictors in the full model were between 1.02 and 4.63, which is much lower than the 5 threshold for significant multicollinearity, and thus did not substantially affect the regression estimates.

Table 6. Hierarchical OLS Regression Predicting Household Financial Resilience

Predictor	Model 1 β	Model 2 β	Model 3 β	Model 4 β
Gender	.006	.022	.036	.033
Education	.060	.033	.021	-.008
Income	.001	.001	.001	.001
Location	-.028	-.020	-.013	-.011
Mobile money experience	.006	.006	.007	.005
Internet access	.148†	.075	.055	.094

AIFS		.184	.055	-.018
DFI			.240	.126
FC				.299
DT				.145
DFI × FC				-.017
R^2	.060	.088	.132	.228
Adjusted R^2	.045	.071	.114	.206
ΔR^2	—	.028	.044	.096
F	4.15	5.38	7.43	10.43

Note. Unstandardized coefficients reported for demographic controls; standardized-scale coefficients reported for focal constructs measured on identical 1–5 metrics. † $p < .10$. $p < .05$. ***$p < .01$.*** *$p < .001$. N = 400.*

4.6 Mediation Analysis

To formally test the mediation hypothesized in H4 and the serial mediation hypothesized in H7, bootstrapped indirect-effects analysis was conducted with 5,000 resamples, controlling for the full set of demographic and infrastructural covariates at each stage of the path model. Table 7 reports the path coefficients and bootstrapped indirect effects. The path from AI-driven digital financial services to digital financial inclusion (path a) was strong and significant ($a = .543$, $p < .001$). The path from digital financial inclusion to financial capability (path d), controlling for AI-driven digital financial services, was likewise strong and significant ($d = .397$, $p < .001$), supporting H5. The path from digital financial inclusion to household financial resilience (path b), controlling for AI-driven digital financial services and financial capability, was significant ($b = .125$, $p = .020$), and the path from financial capability to household financial resilience (path c), controlling for the same covariates, was significant and substantively the largest of the resilience-stage paths ($c = .297$, $p < .001$), supporting H6.

The simple indirect effect of AI-driven digital financial services on household financial resilience through digital financial inclusion alone ($a \times b$) was .068, with a 95% bootstrapped confidence interval of [.010, .129], which excludes zero and is therefore statistically significant, supporting H4. The serial indirect effect through digital financial inclusion and then financial capability ($a \times d \times c$) was .062, with a 95% bootstrapped confidence interval of [.038, .090], which likewise excludes zero, supporting H7. Together, the two significant indirect pathways accounted for approximately 71% of the total effect of AI-driven digital financial services on household financial resilience (total effect c-total = .184, 95% CI [.083, .284]), while the residual direct effect ($c' = .046$, ns, in the model excluding digital trust) was small and statistically non-significant. This pattern constitutes strong evidence of full, sequential mediation: AI-driven digital financial services shape household financial resilience almost entirely through their effect on digital financial inclusion and, subsequently, financial capability, rather than through any residual direct channel.

Table 7. Bootstrapped Mediation Results (5,000 Resamples)

Path	**Coefficient**	**p**	**95% CI**	
a: AIFS → DFI	.543	<.001	—	
d: DFI → FC (\	AIFS)	.397	<.001	—
b: DFI → HFR (\	AIFS, FC)	.125	.020	—
c: FC → HFR (\	AIFS, DFI)	.297	<.001	—
c-total: AIFS → HFR (total)	.184	<.001	[.083, .284]	

c′: AIFS → HFR (direct, \	DFI, FC)	.046	.368 (ns)	—
Indirect: AIFS → DFI → HFR (a × b)	.068	—	[.010, .129]	
Indirect (serial): AIFS → DFI → FC → HFR (a × d × c)	.062	—	[.038, .090]	

Note: *Bootstrapped 95% confidence intervals that exclude zero indicate a statistically significant indirect effect. All models control for gender, education, income, location, mobile money experience, and internet access. ns = not significant*

4.7 Moderation Analysis

Table 8 presents the test of digital trust as a moderator of the relationship between AI-driven digital financial services and digital financial inclusion (H8). The interaction term (AI-driven digital financial services × digital trust) was negative in direction but statistically non-significant (β = -.087, p = .271), indicating that, contrary to H8, digital trust did not significantly alter the strength of the relationship between AI-driven digital financial services and digital financial inclusion in this sample. Simple slope analysis illustrates the substantive size of this non-significant pattern: the estimated effect of AI-driven digital financial services on digital financial inclusion was .597 at one standard deviation below the mean of digital trust, .546 at the mean, and .494 at one standard deviation above the mean a modest and statistically non-significant divergence across levels of digital trust. H8 is therefore not supported. Notably, however, digital trust retained a significant, positive, direct effect on household financial resilience in the fully specified model reported in Table 6 (β = .145, p = .002), indicating that digital trust matters as an independent contributor to resilience even though it does not significantly condition the strength of the AI-driven-services-to-inclusion pathway.

Table 8. Moderation Test: Digital Trust on the AIFS–DFI Relationship

Predictor	**β**	**SE**	**t**	**p**
AIFS	.546	.053	10.37	<.001
Digital Trust (DT)	-.010	.047	-0.22	.827
AIFS × DT	-.087	.079	-1.08	.271
R^2	.287			
F	15.64			

Note. Model controls for gender, education, income, location, mobile money experience, and internet access. Simple slopes: -1SD DT = .597; Mean DT = .546; +1SD DT = .494 (all controlling for covariates).

4.8 Regression Diagnostics

To confirm that the OLS assumptions underlying the reported models were satisfied, the residuals of the fully specified resilience model (Table 6, Model 4) were subjected to formal diagnostic testing. The Shapiro Wilk test failed to reject the null hypothesis of normally distributed residuals, W = .996, p = .390, and residual skewness (-.045) and kurtosis (-.386) were both close to zero, supporting the normality assumption. The Breusch–Pagan test failed to reject the null hypothesis of homoscedasticity, LM = 7.63, p = .665, indicating no evidence of problematic heteroscedasticity. The Durbin–Watson statistic was 2.085, close to the value of 2.0 indicative of no first-order autocorrelation among residuals. Taken together with the variance inflation factors reported in Section 4.5, these diagnostics confirm that the assumptions underlying the study's OLS-based hypothesis tests were adequately satisfied.

4.9 Summary of Hypothesis Testing

Table 9 summarizes the outcome of hypothesis testing across the eight hypotheses advanced in Section 2. Six of the eight hypotheses (H1, H2, H3, H4, H5, H6, H7 seven in total) received empirical support, while the moderation hypothesis (H8) was not supported.

Table 9. Summary of Hypothesis Testing Results

Hypothesis	Relationship	Result
H1	AIFS → DFI (positive)	Supported
H2	DFI → HFR (positive)	Supported
H3	AIFS → HFR, direct (positive)	Supported (total effect); attenuates with mediators
H4	DFI mediates AIFS → HFR	Supported
H5	DFI → FC (positive)	Supported
H6	FC → HFR (positive)	Supported
H7	DFI and FC serially mediate AIFS → HFR	Supported
H8	DT moderates AIFS → DFI	Not supported

5. DISCUSSION

The aim of this study was to investigate whether digital financial inclusion and financial capability act as mediators between the use of AI-driven digital financial services and financial resilience of Sierra Leonean households and whether digital trust is a moderator between the use of AI-driven financial services and the pathway to digital financial inclusion. The study found support for seven of its eight hypotheses, which suggest that artificial intelligence enhances household resilience mainly through formal digital financial inclusion and, in turn, through financial capability to leverage the formal financial inclusion. There was no significant direct pathway between AI and household resilience that was not mediated by either formal digital financial inclusion or financial capability to use it.

The results of this study, which confirm that AI-powered digital financial services have a strong predictive power for digital financial inclusion (H1), are consistent with a large amount of previous evidence. The present study's path coefficient (a = .543) indicates that the functions enabled by AI are already seen by Sierra Leonean users as a meaningful differentiator of the digital financial services they receive, rather than as a technology that is invisible to them in the background. (Rawat, Sharma, et al., 2023b) state that path coefficient architectures of intelligent digital financial inclusion systems are becoming a key aspect of how financial institutions in the Industry 5.0 paradigm structure their service delivery. This is in line with (Mhlanga, 2025a) argument that AI is a catalyst for wealth creation because it extends the number of financially excluded individuals that formal institutions can and want to serve, replacing the manual underwriting process that has historically excluded low-income, thin-file borrowers with algorithmic inference. The size of the effect observed here one of the largest of any structural path in the model indicates that, at least in the Sierra Leonean context, the perception of AI-enabled functionality is a strong signal of a provider's overall digital sophistication, which respondents seem to equate directly with increased use of digital financial channels.

The results of the study support the hypothesis that digital financial inclusion is significantly predictive of household financial resilience (H2), and that this relationship is a significant explanation of the impact of AI-driven digital financial services on resilience (H4), going beyond the enterprise level evidence. The present study's household-level replication of this pattern in Sierra Leone extends the resilience-enhancing role of digital financial inclusion beyond enterprise contexts and beyond South Asian economies to the financial decision-making of households in a significantly lower-income, post-conflict economy. The full-mediation pattern documented in Table 6 in which AI-driven digital financial services' direct effect on resilience collapses to non-significance once digital financial inclusion is entered provides an important refinement of the existing literature. The present results make a formal test of the downstream welfare effects of AI, and they show that the effect of AI on household resilience in

Sierra Leone is almost exclusively through the inclusion channel, rather than through any capability that AI can provide that is relevant to resilience, but not to financial inclusion.

The serial mediation finding (H7) is an important mechanistic finding that has not been explicitly modelled in much of the current digital financial inclusion literature, as the impact of digital financial inclusion on resilience is significantly mediated by financial capability. (Sharma et al., 2023) argue that the use of digitalized financial management tools is closely associated with users' capacity for effective financial planning, and the results of the present study indicate that digital financial inclusion has a significant positive impact on financial capability ($d = .397$, $p < .001$), suggesting that in Sierra Leone, digital financial inclusion is an experiential learning environment: the more households use formal digital financial services, the more they seem to gain in budgeting confidence and understanding of the products, which in turn leads to increased resilience. This is in line with the poverty-theoretic argument put forward by (Mhlanga, 2022) that digital financial inclusion should not be seen as a binary access indicator, but as a developmental process whereby excluded populations gradually acquire the skills and knowledge required to break out of poverty traps, which the findings in the present study demonstrate through the serial mediation.

The null finding for the moderating effect of digital trust (H8) should not be overlooked. There are a number of possible explanations. Second, digital trust may not be a continuous moderator, but rather a threshold condition: once a certain level of trust is reached, and achieved, to open and use a mobile money account (which the sample's high internet access rate and low average tenure of nearly thirteen months indicate most respondents have reached), additional increases in trust may contribute relatively little to the explanatory power of the strength of the AI-to-inclusion relationship. This interpretation is consistent with the systematic review conducted by (Ghandour, 2021) which revealed that trust and security issues act as a binary gatekeeping barrier to the adoption of AI in banking, and not as a continuum of moderation in the intensity of engagement after adoption. Third, although the interaction term was not significant, the significant direct effect of digital trust on household financial resilience ($\beta = .145$, $p = .002$) suggests that digital trust may be a stand-alone asset for resilience, such as by lowering anxiety or precautionary under-use of digital financial products, and not necessarily a direct amplifier of the impact of AI-driven services on increasing inclusion. This separation between direct resource-based role and conditional, interactive role for trust is in line with the argument put forward by (D. Li & Azman, 2024), who identified that trust concerns had a more direct impact on overall usage and behavioral outcomes of a digital currency system than they did in moderating the relationship between specific technological features and adoption intensity.

The lack of a significant moderating effect of financial capability on the relationship between digital-financial-inclusion and resilience is also informative, as is the strong direct effect of financial capability. The results indicate that financial capability is an independently important, parallel driver of resilience, rather than a capability amplifier that is only effective if inclusion "pays off" in terms of resilience. This aligns with the argument put forward by (H. Mishra & Mishra, 2024) that capability-building interventions can increase resilience at the household level, via channels that are at least partly different from those through which formal access works. In practice, this means that policies focused on increasing digital financial inclusion and policies focused on increasing financial capability should be considered complementary, not mutually exclusive or necessarily sequential, as both independently and significantly predict household resilience.

Lastly, the results are generally in line with the literature that warns of the dangers of AI-based inclusion. However, claims of inclusion based on artificial intelligence should be treated with suspicion as algorithmic systems can in some situations reflect and even reinforce pre-existing exclusionary biases (Qureshi et al., 2021). The present study does not identify such amplification at the household level in Sierra Leone, but rather, AI-powered digital financial services are linked to significantly higher levels of inclusion, capability, and indirectly, resilience of the sample as a whole. However, the study's cross-sectional design does not eliminate the possibility that the households that are most positive about AI-driven services are systematically different in ways not measured in the study from those that are not, as is discussed below in the limitations section. The role of digital technology in entrepreneurial decision making in agricultural contexts is a good parallel to the present study: digital and AI-enabled financial technologies are found to be most transformative when they interact with users' existing capabilities and decision-making contexts, as (Chen & Yang, 2021) found for the domain of household resilience.

6. THEORETICAL, PRACTICAL, AND POLICY IMPLICATIONS

6.1 Theoretical Implications

This study makes several contributions to digital financial inclusion theory. First, by explicitly modelling and empirically confirming a serial mediation pathway AI-driven services to inclusion to capability to resilience the study extends financial inclusion theory beyond its traditional access-usage-quality framing to incorporate an explicit developmental, capability-building dimension, in the spirit of the poverty-theoretic reframing proposed by (Mhlanga, 2022). Second, by demonstrating that the direct effect of AI-driven digital financial services on household resilience is fully attenuated once inclusion and capability are accounted for, the study provides empirical discipline to a literature that has often treated artificial intelligence's welfare effects as self-evident; the present findings instead specify the precise mechanism through which such effects are realized, addressing the call by (Grover et al., 2025) for more granular, mechanism-based evidence on how AI narrows socioeconomic gaps. Third, the study's null finding regarding digital trust's moderating role, set alongside its significant direct effect on resilience, contributes a theoretically important distinction between trust as a conditional amplifier of technology effectiveness and trust as an independent resilience resource, a distinction that future theoretical models of technology-enabled financial inclusion should incorporate explicitly rather than treating trust as a generic, undifferentiated moderator. Fourth, the study extends the predominantly Asian and enterprise-level evidence base exemplified by the China-focused studies of (Shang, 2024), (Wang et al., 2022), and (Q. Zhou et al., 2023) to a household-level, Sub-Saharan African, post-conflict economic context, thereby broadening the external validity of digital financial inclusion theory. This broadening is timely: the volume of conference-level scholarship on digital financial inclusion and artificial intelligence continues to grow rapidly, as reflected in the range of studies compiled in the "Proceedings of the Guangdong-Hong Kong-Macao Greater Bay Area International Conference" (2024), yet this expanding body of work remains heavily concentrated in East Asian economic settings, underscoring the value of the household-level, West African evidence generated here.

6.2 Practical Implications for Fintech Providers

For fintech providers and mobile network operators active in Sierra Leone, the findings suggest that continued investment in visible, user-facing AI-enabled functionality automated credit assessment, conversational customer support, and biometric verification is likely to yield tangible inclusion dividends, given the strong path coefficient observed between AI-driven digital financial services and digital financial inclusion. However, the results caution against assuming that expanded access alone will translate into improved household resilience. Because the inclusion-to-resilience pathway operates substantially through financial capability, providers stand to gain more from resilience-relevant customer outcomes and, plausibly, from more sustainable long-term customer relationships by pairing AI-driven service expansion with embedded financial education features, such as in-app budgeting tools, personalized spending insights, or gamified financial literacy modules, rather than treating access expansion and capability building as separate workstreams. (Ozili, 2025b) notes that AI's applications in financial services span risk management, fraud detection, and customer experience; the present findings suggest that providers who extend these applications to explicitly support capability-building, rather than confining AI's role to backend risk functions, are best positioned to convert inclusion into measurable improvements in customers' resilience.

6.3 Policy Implications for Regulators and Development Partners

For the Bank of Sierra Leone and allied financial sector regulators, the study's findings support continued regulatory facilitation of AI-enabled digital financial services, given the absence of evidence that such services systematically undermine inclusion outcomes at the household level in this sample. At the same time, the null moderation finding for digital trust suggests that trust-building regulatory interventions such as consumer-protection frameworks, algorithmic transparency requirements, and dispute-resolution mechanisms should be pursued as a means of directly strengthening household resilience, rather than being positioned primarily as a lever for accelerating AI-driven inclusion, since the present evidence indicates that trust's resilience benefits are more direct than conditional. For development partners and financial-inclusion-focused non-governmental organizations, the study's serial mediation findings imply that programmes combining digital access facilitation (for example, subsidized smartphone or mobile money onboarding) with structured financial capability training are likely to generate larger resilience gains than either intervention pursued alone. (Mhlanga, 2025b) analysis of policy responses for advancing digital financial inclusion across Africa similarly argues that the complexities of the African financial inclusion landscape require multi-pronged policy responses rather than single-lever interventions, a conclusion the present study's statistical findings reinforce with household-level evidence specific to Sierra Leone. Finally, given that internet access, though widespread in this sample, remained a significant infrastructural constraint for a meaningful minority of respondents (15.75%), continued investment in rural connectivity infrastructure remains a necessary complement to fintech-sector innovation if the resilience benefits documented here are to be extended to Sierra Leone's most remote and currently excluded households.

7. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Several limitations qualify the interpretation of this study's findings and point toward productive directions for future research. First, the cross-sectional design precludes strong causal inference; while the hypothesized directional pathways are grounded in established theory and the observed pattern of full mediation is consistent with the theorized causal sequence, reverse or reciprocal causal pathways for instance, households with greater existing resilience selecting into greater engagement with AI-driven digital financial services cannot be definitively ruled out. Future research employing longitudinal panel designs, or natural experiments arising from the phased rollout of specific AI-enabled financial products, would allow firmer causal claims to be established. Second, all constructs were measured via respondent self-report, and although the study's Harman's single-factor test and procedural remedies suggest that common method bias did not materially distort the findings, future studies could strengthen causal and construct validity by triangulating self-reported inclusion and resilience measures against objective administrative data, such as verified mobile money transaction records or credit bureau outcomes, an approach exemplified in spirit by the large-scale panel-data methodologies employed by (L. Han & Tian, 2024) and (Z. Feng et al., 2024) in other national contexts.

Third, the study's sampling procedure, while stratified by location and designed to balance practical field constraints against representativeness, relied on intercept and snowball elements that may not fully replicate the properties of a strict probability sample; caution is therefore warranted in generalizing point estimates, as opposed to the study's structural relationships, to the full Sierra Leonean population. Fourth, the moderation analysis tested digital trust only as a moderator of the AI-driven-services-to-inclusion pathway; given the study's finding that digital trust exerts a significant direct effect on resilience, future research should test digital trust as a moderator at additional points in the model for instance, of the inclusion-to-capability or capability-to-resilience pathways to more fully map where trust exerts its conditioning influence. Fifth, this study did not explicitly measure or control for shock exposure (for example, the frequency or severity of recent income shocks experienced by each household), which could plausibly influence both reported resilience and the perceived value of digital financial services; incorporating shock-exposure measures represents a valuable extension for future work, potentially drawing on the kind of systemic-shock-focused framework applied by (H. Mishra & Mishra, 2024) in the context of agricultural food security. Finally, replication of this model across other Sub-Saharan African economies with differing regulatory environments, mobile money ecosystems, and conflict histories would help establish the boundary conditions under which the strong mediating role of digital financial inclusion and financial capability documented here can be expected to hold, extending the cross-country comparative logic exemplified by (Sakyi-Nyarko et al., 2025) in their analysis of the digital-financial-inclusion–trade nexus across multiple African economies.

8. CONCLUSION

This study examined the relationship between AI-driven digital financial services and household financial resilience among 400 households in Sierra Leone, testing digital financial inclusion and financial capability as sequential mediators and digital trust as a moderator. The results demonstrate that AI-driven digital financial services significantly strengthen digital financial inclusion, which in turn significantly strengthens both financial capability and household financial resilience, and that financial capability itself significantly strengthens resilience. The direct effect of AI-driven digital financial services on resilience was fully explained by this serial pathway, indicating that artificial intelligence's contribution to household resilience in Sierra Leone operates chiefly through the formal financial system it draws households into, and through the financial capability that sustained engagement with that system builds, rather than through any independent channel. Digital trust, while not found to significantly moderate the strength of the AI-driven-services-to-inclusion relationship, nonetheless emerged as a significant direct predictor of resilience in its own right. These findings extend digital financial inclusion theory into the artificial intelligence era, provide some of the first rigorously validated household-level evidence from Sierra Leone on this relationship, and offer concrete guidance to fintech providers, regulators, and development partners seeking to translate the rapid expansion of AI-enabled financial technology into durable improvements in household financial resilience across Sierra Leone and comparable low-income, digitally transitioning economies.

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