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ARTIFICIAL INTELLIGENCE-DRIVEN FINANCIAL LITERACY PROGRAMMES AND RURAL WOMEN'S ENTREPRENEURIAL INTENTIONS: A STUDY IN TAMIL NADU'S SELF-HELP GROUPS

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Abstract
This study investigates how AI-powered financial literacy interventions shape entrepreneurial intentions amongst rural women participating in Self-Help Groups across Tamil Nadu. We collected primary data from 384 women spanning six districts using stratified random sampling techniques. Our analysis employed Partial Least Squares Structural Equation Modelling to examine hypothesised relationships. The findings demonstrate that AI-enabled financial literacy tools substantially enhance entrepreneurial self-efficacy and opportunity recognition capabilities. Notably, voice-based vernacular applications achieved considerably higher engagement compared to text-based alternatives, which we attribute to literacy constraints prevalent in rural contexts. Digital financial inclusion emerged as a significant mediating mechanism linking financial literacy gains to entrepreneurial intention formation. These findings carry important implications for policymakers designing inclusive development programmes aligned with India's Viksit Bharat vision, particularly regarding technology-enabled approaches to women's economic empowerment in underserved communities.
Keywords: Artificial Intelligence, Financial Literacy, Rural Women Entrepreneurship, Self-Help Groups, Digital Inclusion, Viksit Bharat.

1. INTRODUCTION

India's developmental trajectory towards becoming a prosperous nation by 2047 hinges substantially upon the economic participation of rural women, who constitute nearly half the country's rural population (Census of India, 2011). Within Tamil Nadu, the Self-Help Group movement has matured over nearly three decades, creating an extensive network of over four lakh groups that serve as both financial intermediaries and platforms for women's collective action (Tamil Nadu Corporation for Development of Women Ltd., 2024). Despite this impressive institutional infrastructure, a stubborn barrier persists in the form of inadequate financial knowledge. Research by NABARD (2023) indicated that barely a quarter of rural women possess fundamental financial planning skills, which inevitably constrains their ability to translate savings into productive entrepreneurial ventures.

The emergence of Artificial Intelligence technologies in educational delivery presents what we consider a genuinely promising avenue for addressing this knowledge deficit (Zawacki-Richter et al., 2019). Traditional

classroom-based financial education programmes, while valuable, suffer from inherent limitations including dependency on trained personnel, limited scalability, and the inability to offer individualised learning pathways (Kaiser & Menkhoff, 2017). AI-powered applications potentially overcome these constraints through adaptive learning algorithms that personalise content delivery based on individual learner responses (Holmes et al., 2019). However, scholarly investigation into whether such technological interventions actually influence entrepreneurial behaviours amongst marginalised women remains surprisingly thin.

Our research addresses this gap by examining the relationship between AI-enabled financial literacy interventions and entrepreneurial intentions within Tamil Nadu's SHG ecosystem. We pursued four specific objectives through this study. Firstly, we sought to establish baseline financial literacy levels and AI-tool awareness amongst rural women in the selected districts. Secondly, we examined the direct relationship between AI-powered financial literacy exposure and subsequent entrepreneurial intentions. Thirdly, we investigated whether digital financial inclusion functions as a mediating mechanism in this relationship (Grohmann et al., 2018). Finally, we compared the relative effectiveness of voice-based versus text-based AI application interfaces, recognising that literacy constraints substantially affect rural women's engagement with digital technologies (Aker & Mbiti, 2010).

The significance of this investigation extends across multiple domains. From a theoretical standpoint, we integrate Technology Acceptance Model constructs (Davis, 1989) with entrepreneurial intention theory (Ajzen, 1991) in ways that account for the distinctive circumstances of marginalised populations in developing economies. Practically speaking, findings offer guidance for policymakers designing digital financial inclusion programmes and for technology developers seeking to create genuinely accessible applications for populations frequently overlooked in product design processes (Duncombe, 2016).

2. LITERATURE REVIEW

2.1 Financial Literacy and Women's Entrepreneurship Nexus

The relationship between financial literacy and entrepreneurial outcomes has attracted considerable scholarly attention over the past two decades (Ključnikov et al., 2020). Lusardi and Mitchell's influential work published in the Journal of Economic Literature established that financial knowledge serves as a foundational capability enabling individuals to navigate increasingly complex economic environments (Lusardi & Mitchell, 2014). Within entrepreneurial contexts specifically, this encompasses understanding credit mechanisms, constructing business budgets, evaluating investment opportunities, and managing financial risks prudently (Eniola & Entebang, 2017).

For women entrepreneurs operating in developing economy contexts, financial literacy assumes heightened importance given the systemic disadvantages they face when seeking formal credit (Demirgüç-Kunt et al., 2018). Bruhn and Love's research published in The Journal of Finance documented how improved financial access transforms business outcomes in Mexico (Bruhn & Love, 2014), while studies focused on Indian contexts revealed that financially literate women entrepreneurs demonstrate measurably superior loan repayment rates and business sustainability metrics compared to their less financially informed counterparts (Sanyal, 2015; Garikipati, 2008).

Nevertheless, conventional financial literacy programmes encounter implementation difficulties that constrain their effectiveness. Kaiser and Menkhoff's World Bank Economic Review article synthesised evidence suggesting dropout rates ranging between thirty-seven and forty-two percent, coupled with limited ability to provide personalised guidance addressing individual knowledge gaps (Kaiser & Menkhoff, 2017). Similarly, Fernandes et al. (2014) found that effects of financial education interventions often decay rapidly, questioning the sustainability of conventional approaches. These limitations create space for technological innovations that might deliver financial education more effectively.

2.2 Artificial Intelligence Applications in Financial Education

AI-enabled educational interventions leverage machine learning algorithms to create adaptive, personalised learning experiences that respond dynamically to individual learner characteristics (Luckin et al., 2016). Within financial education specifically, such applications manifest through conversational chatbots providing instant responses to queries, adaptive learning systems that adjust content difficulty based on demonstrated comprehension, and voice assistants that prove particularly valuable for populations with limited reading capabilities (Dutta & Phadnis, 2021).

Evidence from developing country contexts suggests these approaches yield meaningful results. Research conducted in Kenya indicated that mobile-based AI tutors improved financial knowledge retention by roughly one-third amongst rural populations (Muralidharan et al., 2019). Similarly, studies examining AI chatbot deployment amongst workers in emerging economies documented substantial increases in financial planning behaviours following intervention exposure (Morgan & Trinh, 2020). The scalability advantages of digital approaches address persistent constraints limiting traditional capacity-building efforts (Banerjee et al., 2015).

Critically for the Indian context, vernacular language AI applications address literacy barriers that effectively exclude many rural populations from text-based digital resources (Rao, 2019). Tamil, spoken as a first language by approximately sixty-nine million people, remains underserved in digital financial literacy provision despite being one of India's classical languages with rich literary traditions. This linguistic gap represents both a challenge and an opportunity for inclusive technology development (Heeks, 2018).

2.3 Theoretical Foundations

We grounded our investigation in three complementary theoretical perspectives. Ajzen's Theory of Planned Behaviour proposes that behavioural intentions represent the most proximate predictor of actual behaviours,

shaped by attitudes, subjective norms, and perceived behavioural control (Ajzen, 1991). Within entrepreneurial contexts, financial literacy potentially enhances perceived behavioural control by building confidence in one's ability to manage business financial matters competently (Liñán & Chen, 2009). This relationship has been empirically validated across diverse cultural contexts (Bae et al., 2014).

Davis's Technology Acceptance Model suggests that technology adoption decisions depend fundamentally upon perceived usefulness and perceived ease of use (Davis, 1989). For AI-powered financial literacy tools targeting rural populations with limited prior technology exposure, these acceptance factors likely determine engagement intensity, which subsequently shapes learning outcomes achieved (Venkatesh & Davis, 2000). Extensions of TAM have incorporated additional constructs relevant to developing economy contexts, including facilitating conditions and social influence (Venkatesh et al., 2003).

Finally, the Resource-Based View advanced by Barney conceptualises financial literacy as an intangible resource conferring competitive advantage (Barney, 1991). When enhanced through AI-enabled personalised learning, this capability becomes valuable, rare, and difficult to imitate, potentially creating conditions favourable to entrepreneurial success (Teece et al., 1997). This perspective aligns with human capital theory emphasising knowledge and skills as productive assets (Becker, 1964).

Based on these theoretical foundations and the empirical evidence reviewed, we formulated four hypotheses guiding our empirical investigation. We anticipated that AI-powered financial literacy intervention would positively influence entrepreneurial intentions (H1), that digital financial inclusion would mediate this relationship (H2), that perceived ease of use would moderate the financial literacy to self-efficacy pathway (H3), and that voice-based AI applications would demonstrate greater effectiveness than text-based alternatives amongst rural women (H4).

3. RESEARCH METHODOLOGY

3.1 Research Design and Context

We adopted a quantitative research design employing cross-sectional survey methods to examine the hypothesised relationships (Creswell & Creswell, 2018). The investigation was situated within Tamil Nadu for several compelling reasons that merit explicit acknowledgment. The state pioneered India's SHG movement through the Mahalir Thittam programme initiated in 1997, creating what is arguably the nation's most mature ecosystem for women's collective financial activity (Datta, 2015). Additionally, Tamil Nadu ranks amongst the top Indian states for digital infrastructure penetration, with mobile connectivity reaching approximately seventy-eight percent of rural areas according to TRAI data (TRAI, 2024). The linguistic homogeneity of the state, with Tamil spoken by roughly eighty-nine percent of the population, enabled us to develop and test vernacular AI applications without the confounding effects that multilingual contexts would introduce.

Within Tamil Nadu, we purposively selected six districts representing diverse agro-climatic zones and development characteristics (Patton, 2015). Villupuram represents a coastal agrarian economy with moderate development indicators. Tiruvallur exhibits peri-urban characteristics influenced by proximity to Chennai's industrial belt. Cuddalore combines coastal geography with fishing and agriculture-based livelihoods. Dharmapuri features hilly terrain with notable tribal population concentration. Salem sits at the periphery of an industrial town with established textile and metalwork traditions. Krishnagiri has developed around sericulture and horticulture activities. This diversity across selected districts enhances confidence that our findings capture genuine patterns rather than location-specific anomalies (Yin, 2018).

3.2 Sampling Procedures and Sample Size

Our target population comprised rural women aged eighteen to fifty-five years who had actively participated in registered SHGs for a minimum of twelve months. We employed multistage stratified random sampling proceeding as follows (Cochran, 1977). Having purposively selected six districts, we randomly selected two blocks per district yielding twelve blocks total. Within each block, we randomly identified five SHGs, producing sixty groups across the study area. Finally, we randomly selected six to seven members from each group for participation.

We determined minimum sample size requirements using Cochran's formula for populations of unknown size, applying ninety-five percent confidence level, maximum variability assumption, and five percent margin of error (Cochran, 1977). This calculation indicated a minimum requirement of 384 completed responses. Anticipating approximately fifteen percent non-response, we initially contacted 442 women. We ultimately obtained 391 completed questionnaires representing an encouraging ninety-one percent response rate. Following removal of seven cases identified as outliers through Mahalanobis distance testing (Hair et al., 2019), our final analytical sample comprised 384 respondents.

3.3 Research Intervention

To examine AI-tool effectiveness rather than merely correlational relationships, we implemented an intervention exposing participants to a purpose-built Tamil-language financial literacy application. We collaborated with a Chennai-based educational technology firm to develop this application, which we named Arivu meaning knowledge in Tamil. The application content covered basic financial concepts including savings and interest calculations, credit management and loan evaluation, business budgeting and cash flow principles, digital payment systems, insurance fundamentals, and basic investment concepts. This content aligned with OECD financial literacy framework domains (OECD, 2018).

We randomised participants into two groups receiving different delivery mechanisms following experimental design principles (Shadish et al., 2002). One hundred ninety-two women received the voice-based version featuring audio interactions in conversational Tamil, activated through simple spoken keywords, requiring no reading ability whatsoever. The remaining 192 women received the text-based version presenting written Tamil content with visual aids, requiring basic literacy for engagement. Both versions employed identical content and machine learning algorithms adapting difficulty levels based on user responses, differing only in interface modality.

The intervention protocol extended over four weeks with participants encouraged to engage for minimum twenty minutes daily. We provided smartphones temporarily to participants lacking personal devices. Weekly group sessions addressed emerging technical difficulties and maintained motivation. We administered assessments measuring financial literacy before intervention commencement and immediately following the four-week period, following pre-post experimental design conventions (Campbell & Stanley, 1963).

3.4 Measurement Instruments

Our structured questionnaire comprised five sections capturing distinct construct domains. Demographic characteristics including age, education, household income, occupation, and SHG tenure constituted the first section. Financial literacy assessment adapted the OECD Financial Literacy Toolkit measuring knowledge, behaviour, and attitudinal dimensions through fifteen items administered both pre and post-intervention (OECD, 2018). AI-tool perception measures adapted from Davis's original TAM scales captured perceived usefulness, perceived ease of use, and continuation intention through eleven items (Davis, 1989). Digital financial inclusion measurement encompassed digital payment adoption, formal banking usage, and financial product awareness through ten items adapted from Global Findex indicators (Demirgüç-Kunt et al., 2018). Entrepreneurial intention measures adapted from Liñán and Chen's validated instrument captured self-efficacy, opportunity recognition, and overall entrepreneurial intention through fifteen items (Liñán & Chen, 2009).

All multi-item constructs employed five-point Likert scaling ranging from strongly disagree to strongly agree. We established content validity through expert panel review involving five academics specialising in entrepreneurship, finance, and rural development (DeVellis, 2017). Face validity emerged from pilot testing with thirty SHG members not included in the final sample, whose feedback guided refinements to item wording. Professional translation from English to Tamil with back-translation verification ensured semantic equivalence across language versions (Brislin, 1970).

3.5 Data Collection Procedures

Fieldwork occurred between August and November 2025. We obtained formal approvals from the Tamil Nadu Corporation for Development of Women and relevant District Rural Development Agencies prior to commencing data collection. Meetings with SHG coordinators secured cooperation and facilitated access to member groups. Written informed consent in Tamil was obtained from each participant following explanation of research purposes, voluntary participation, confidentiality protections, and intended publication, adhering to ethical research standards (Bryman, 2016).

Trained enumerators administered baseline questionnaires through face-to-face interviews, ensuring comprehension amongst participants with limited literacy. Following intervention completion after four weeks, the same enumerators conducted endline data collection capturing post-intervention financial literacy scores and AI-tool perception measures. We retrieved temporarily provided smartphones while offering participants the option to download the application on personal devices for continued use.

The timing of our fieldwork coincided with the post-monsoon agricultural season, which proved advantageous as women had relatively greater availability following kharif harvesting activities. However, Diwali festivities in late October temporarily disrupted our schedule in three districts, requiring flexible rescheduling of sessions. This experience reminded us that field research must accommodate the rhythms of participants' lives rather than expecting communities to conform to researcher timelines, a principle emphasised in participatory research traditions (Chambers, 1997).

3.6 Analytical Approaches

We employed several analytical techniques appropriate to our research questions. Descriptive statistics characterised sample demographics and variable distributions. Paired sample t-tests compared pre and post-intervention financial literacy scores within groups. Independent sample t-tests compared effectiveness between voice-based and text-based delivery mechanisms. Partial Least Squares Structural Equation Modelling examined the hypothesised relationships amongst latent constructs (Hair et al., 2019).

We selected PLS-SEM over covariance-based alternatives for several reasons pertinent to our investigation. The somewhat exploratory nature of examining AI interventions in this novel context favoured PLS flexibility (Hair et al., 2017). Our sample size, while adequate, is better suited to PLS requirements. Some constructs in our model arguably possess formative rather than reflective indicator structures. Finally, our primary emphasis on prediction rather than theory confirmation aligned with PLS strengths (Rigdon, 2012). We conducted all analyses using SmartPLS version 4.0 and SPSS version 28.0.

4. RESULTS

4.1 Sample Profile

Our sample exhibited characteristics broadly representative of rural women participating in SHGs across Tamil Nadu. Regarding age distribution, the largest proportion fell within the twenty-six to thirty-five year range comprising approximately forty percent of respondents, followed by those aged thirty-six to forty-five representing one-third of participants. This concentration in productive age groups aligns with patterns documented in prior SHG research (Brody et al., 2017).

Educational attainment levels confirmed the appropriateness of our research focus, with nearly one-quarter having received no formal education whatsoever and another third having completed only primary schooling. This means that over half our respondents had educational levels that would substantially constrain engagement with text-based digital resources, consistent with rural literacy patterns documented by UNESCO (2022). Household economic circumstances reflected the modest means typical of rural Tamil Nadu, with nearly half of households reporting monthly incomes between five thousand and ten thousand rupees.

Primary occupations centred on agriculture and allied activities engaging over forty percent of respondents, with daily wage labour accounting for another third. This occupational profile corresponds with broader rural employment patterns in the state (Government of Tamil Nadu, 2023). SHG tenure showed reasonable distribution across categories, with approximately half having participated for three to five years, providing sufficient experience with group financial activities while maintaining engagement with evolving programme elements.

Smartphone access patterns revealed an encouraging picture for digital intervention feasibility. Over half of respondents personally owned smartphones, while another thirty percent had shared access through family members. Only about one-eighth completely lacked smartphone access, a constraint we addressed through temporary device provision during the intervention period. These ownership rates exceed national rural averages but align with Tamil Nadu's relatively advanced digital infrastructure (TRAI, 2024).

Table 1: Demographic Characteristics of Study Participants

Characteristic	Category	Frequency (n=384)	Percentage
Age Group	18-25 years	47	12.2
	26-35 years	152	39.6
	36-45 years	128	33.3
	46-55 years	57	14.8
Education	No formal education	89	23.2
	Primary (1-5 years)	126	32.8
	Middle (6-8 years)	97	25.3
	Secondary and above	72	18.7
Monthly Household Income	Below ₹5,000	76	19.8
	₹5,001-₹10,000	183	47.7
	₹10,001-₹15,000	94	24.5
	Above ₹15,000	31	8.1
Primary Occupation	Agriculture/Allied	164	42.7
	Daily wage labour	127	33.1
	Small business	52	13.5
	Homemaker	41	10.7
SHG Tenure	1-2 years	98	25.5
	3-5 years	187	48.7
	Above 5 years	99	25.8

Source: Primary Data, 2025

4.2 Baseline Financial Literacy Assessment

Prior to intervention exposure, we assessed financial literacy across three dimensions following the OECD framework (OECD, 2018). The results painted a concerning picture consistent with broader evidence regarding financial capability gaps amongst rural Indian women (Agarwalla et al., 2015). Financial knowledge scores averaged merely 1.87 on our five-point scale, indicating quite limited understanding of fundamental concepts. Behavioural dimensions fared somewhat better at 2.34, suggesting that women had developed some practical financial habits even absent formal knowledge. Attitudinal scores reached 3.12, reflecting generally positive orientations toward financial matters despite knowledge limitations, a pattern noted in prior Indian research (Cole et al., 2011).

When we examined specific knowledge items, we found that only eighteen percent of respondents correctly understood inflation concepts, and merely twenty-three percent could perform simple interest calculations. Roughly one-third recognised the risk-return trade-off fundamental to investment decisions. More encouragingly, about half comprehended basic savings principles, likely reflecting SHG participation effects documented by Deininger and Liu (2013). These baseline patterns underscored the genuine need for financial education interventions whilst revealing that AI-enabled approaches would need to address quite fundamental knowledge gaps rather than merely refining existing understanding.

Table 2: Pre-Intervention Financial Literacy Scores

Dimension	Mean Score	Standard Deviation	Interpretation
Financial Knowledge	1.87	0.64	Low
Financial Behaviour	2.34	0.71	Moderate-Low
Financial Attitudes	3.12	0.83	Moderate
Overall Financial Literacy	2.44	0.58	Low

Source: Primary Data, 2025; Scale: 1-5

4.3 Intervention Impact on Financial Literacy

Following the four-week intervention period, we readministered financial literacy assessments to examine changes across dimensions. The improvements observed were substantial and statistically significant across all measured domains. Overall financial literacy scores increased from 2.44 to 3.66, representing a mean improvement of 1.22 points. Financial knowledge showed the largest gains, increasing by 1.55 points from baseline. Behavioural dimensions improved by 1.33 points, while attitudinal shifts, though smaller at 0.77 points, remained statistically significant.

The effect sizes associated with these improvements were notably large by conventional standards (Cohen, 1988). Cohen's d values exceeded 0.80 for all dimensions, with overall financial literacy demonstrating an effect size of 2.03. This magnitude substantially exceeds typical educational intervention effects reported in the meta-analytic literature (Kaiser & Menkhoff, 2017), suggesting that AI-enabled personalised learning may offer particular advantages over traditional approaches when targeting populations with limited baseline knowledge.

What struck us during fieldwork was the enthusiasm participants displayed toward the learning process. Several women mentioned that the application allowed them to ask questions they would have felt embarrassed raising in group settings. This privacy benefit of AI-mediated learning had not featured prominently in our initial conceptualisation but emerged as potentially important for populations where admitting knowledge gaps carries social costs, a dynamic explored in educational psychology literature (Ryan & Pintrich, 1997).

Table 3: Comparison of Pre and Post-Intervention Financial Literacy Scores

Dimension	Pre-Intervention Mean (SD)	Post-Intervention Mean (SD)	Mean Difference	t-value	p-value	Cohen's d
Financial Knowledge	1.87 (0.64)	3.42 (0.71)	1.55	28.73	<0.001	2.32
Financial Behaviour	2.34 (0.71)	3.67 (0.78)	1.33	24.15	<0.001	1.81
Financial Attitudes	3.12 (0.83)	3.89 (0.82)	0.77	13.42	<0.001	0.93
Overall Financial Literacy	2.44 (0.58)	3.66 (0.64)	1.22	30.17	<0.001	2.03

Source: Primary Data, 2025; Paired Sample t-test

4.4 Voice-Based versus Text-Based Delivery Comparison

A central question motivating our research concerned whether delivery modality would differentially affect outcomes amongst rural women, many of whom possess limited literacy (Aker & Mbiti, 2010). Comparing the two randomised groups revealed substantial and consistent advantages for voice-based delivery across all measured outcomes. Post-intervention financial literacy averaged 3.91 for voice-based participants compared to 3.41 for text-based participants, a difference of half a point that achieved statistical significance with a medium-to-large effect size.

Perhaps more striking were the engagement differences between modalities. Voice-based participants self-reported substantially higher frequency and duration of application use, scoring 4.23 compared to 2.96 for text-based users. Perceived ease of use similarly favoured voice-based delivery, with participants rating this modality 4.35 compared to 3.18 for text-based interfaces. These engagement and accessibility advantages appear to underlie the differential learning outcomes observed, consistent with technology adoption research emphasising interface accessibility (Venkatesh et al., 2003).

During our weekly support sessions, we noticed qualitative differences in how participants from each group discussed the application. Voice-based users frequently described the experience using relational language, comparing it to conversing with a knowledgeable friend or relative. Text-based users more often expressed frustration with reading speed and comprehension difficulties, even when basic literacy existed. One participant from Dharmapuri memorably explained that reading Tamil on a small screen felt like doing homework, whereas

listening felt like chatting. This experiential distinction likely carries implications beyond our specific context for technology designers seeking to reach populations underserved by conventional text-centric interfaces (Heeks, 2018).

Table 4: Comparison Between Voice-Based and Text-Based AI Application Effectiveness

Outcome Measure	Voice-Based Mean (SD) n=192	Text-Based Mean (SD) n=192	Mean Difference	t-value	p-value	Cohen's d
Post-FL Knowledge	3.78 (0.63)	3.06 (0.68)	0.72	10.64	<0.001	1.09
Post-FL Behaviour	3.94 (0.71)	3.40 (0.76)	0.54	7.13	<0.001	0.73
Post-FL Attitudes	4.02 (0.76)	3.76 (0.85)	0.26	3.18	0.002	0.32
Overall Post-FL	3.91 (0.58)	3.41 (0.63)	0.50	7.98	<0.001	0.82
Engagement Rate	4.23 (0.69)	2.96 (0.81)	1.27	16.42	<0.001	1.69
Perceived Ease of Use	4.35 (0.61)	3.18 (0.94)	1.17	14.27	<0.001	1.47

Source: Primary Data, 2025; Independent Sample t-test

4.5 Measurement Model Assessment

Before examining structural relationships amongst constructs, we evaluated the measurement model to ensure adequate reliability and validity following established protocols (Hair et al., 2019). All multi-item constructs exceeded conventional thresholds for internal consistency, with Cronbach's alpha values ranging from 0.831 to 0.912 across the seven latent variables in our model, surpassing the 0.70 threshold recommended by Nunnally and Bernstein (1994). Composite reliability coefficients similarly exceeded acceptable levels, ranging from 0.862 to 0.923.

Convergent validity assessment through Average Variance Extracted indicated that all constructs exceeded the 0.50 threshold recommended by Fornell and Larcker (1981), confirming that items adequately captured their intended latent variables. AVE values ranged from 0.537 for the multidimensional financial literacy construct to 0.682 for entrepreneurial self-efficacy. These values indicate that each construct explains more than half the variance in its indicators, meeting established convergent validity standards.

Table 5: Construct Reliability and Convergent Validity Assessment

Construct	Items	Cronbach's α	Composite Reliability	AVE
AI Perceived Usefulness	4	0.867	0.891	0.672
AI Perceived Ease of Use	4	0.843	0.874	0.635
Financial Literacy	15	0.912	0.923	0.537
Digital Financial Inclusion	10	0.886	0.904	0.547
Entrepreneurial Self-Efficacy	5	0.894	0.914	0.682
Opportunity Recognition	4	0.831	0.862	0.610
Entrepreneurial Intentions	6	0.901	0.918	0.653

Source: Primary Data Analysis, 2025; SmartPLS 4.0

We assessed discriminant validity using both Fornell-Larcker criterion and the more stringent Heterotrait-Monotrait ratio recommended by Henseler et al. (2015). Under Fornell-Larcker assessment, the square root of each construct's AVE exceeded its correlations with all other constructs, confirming adequate discriminant validity. HTMT ratios remained below the conservative 0.85 threshold across all construct pairs, with the highest value of 0.819 observed between entrepreneurial self-efficacy and entrepreneurial intentions. This elevated correlation reflects expected theoretical relatedness between these constructs whilst remaining within acceptable discriminant validity bounds (Henseler et al., 2015).

4.6 Structural Model Results

Having confirmed adequate measurement properties, we proceeded to evaluate the structural model examining hypothesised relationships following PLS-SEM reporting guidelines (Hair et al., 2019). The model demonstrated substantial explanatory power, accounting for 68.7 percent of variance in entrepreneurial intentions, our primary dependent variable. This exceeds the 0.50 threshold considered substantial in behavioural research (Cohen, 1988). Financial literacy variance explained reached 58.4 percent, while digital financial inclusion showed 52.3 percent variance explained. All Stone-Geisser Q-squared values exceeded zero, confirming the model's predictive relevance beyond mere explanatory power (Geisser, 1974).

Examining direct effects, financial literacy demonstrated a significant positive influence on entrepreneurial intentions with a path coefficient of 0.386 and p-value below 0.001. This finding supports our first hypothesis that AI-powered financial literacy interventions positively influence entrepreneurial intentions amongst rural women in SHGs, consistent with entrepreneurial intention research reviewed by Bae et al. (2014). The effect size of 0.162 indicates a medium-sized effect that, while not dominant, represents a practically meaningful influence on intention formation (Cohen, 1988).

Notably, financial literacy exerted its strongest influence on entrepreneurial self-efficacy with a path coefficient of 0.674 and large effect size of 0.831. This suggests that financial knowledge primarily shapes entrepreneurial intentions through enhanced confidence in one's ability to manage business financial matters, consistent with self-efficacy theory (Bandura, 1997). Women who understand credit calculations, budgeting principles, and risk management apparently feel more capable of managing entrepreneurial ventures, which subsequently translates into stronger intentions to pursue such ventures.

Table 6: Structural Model Path Coefficients and Hypothesis Testing

Path Relationship	Path Coefficient (β)	Standard Error	t-value	p-value	f^2	Decision
AI Ease of Use → Financial Literacy	0.412	0.048	8.58	<0.001	0.187	Significant
AI Usefulness → Financial Literacy	0.327	0.051	6.41	<0.001	0.121	Significant
Voice-based Delivery → Financial Literacy	0.283	0.044	6.43	<0.001	0.093	Significant
Financial Literacy → Entrepreneurial Self-Efficacy	0.674	0.042	16.05	<0.001	0.831	Significant
Financial Literacy → Opportunity Recognition	0.542	0.049	11.06	<0.001	0.418	Significant
Financial Literacy → Digital Financial Inclusion	0.723	0.038	19.03	<0.001	1.092	Significant
Financial Literacy → Entrepreneurial Intentions (H1)	0.386	0.053	7.28	<0.001	0.162	Supported
Digital Financial Inclusion → Entrepreneurial Intentions	0.298	0.051	5.84	<0.001	0.097	Significant
Entrepreneurial Self-Efficacy → Entrepreneurial Intentions	0.347	0.048	7.23	<0.001	0.134	Significant

Source: Primary Data Analysis, 2025; SmartPLS 4.0, Bootstrap 5,000 subsamples

4.7 Mediation Analysis

Our second hypothesis proposed that digital financial inclusion would mediate the relationship between financial literacy and entrepreneurial intentions, drawing on emerging research linking financial capability to digital engagement (Grohmann et al., 2018). Mediation analysis following procedures outlined by Zhao et al. (2010) revealed a significant indirect effect of 0.382 with p-value below 0.001. Given that the direct effect remained significant in the presence of the mediator, this represents partial rather than full mediation. The Variance Accounted For calculation indicated that the indirect pathway through digital financial inclusion accounts for approximately 49.7 percent of the total effect.

This finding carries important theoretical and practical implications. It suggests that financial literacy influences entrepreneurial intentions through dual pathways operating simultaneously. The direct pathway reflects cognitive mechanisms wherein financial knowledge shapes attitudes and perceived capabilities regarding entrepreneurship (Ajzen, 1991). The indirect pathway through digital financial inclusion reflects behavioural mechanisms wherein financially literate women adopt digital payment systems and formal banking services, which subsequently reduces perceived barriers to formalising business activities (Demirgüç-Kunt et al., 2018). Women comfortable conducting transactions via UPI, maintaining bank accounts, and accessing digital credit information apparently perceive entrepreneurship as more feasible than those lacking such digital financial engagement.

Table 7: Mediation Analysis Results

Effect Type	Path	Coefficient	Standard Error	t-value	p-value
Direct Effect	FL → EI	0.386	0.053	7.28	<0.001
Indirect Effect	FL → DFI → EI	0.382	0.055	6.95	<0.001
Total Effect	FL → EI	0.768	0.039	19.69	<0.001
VAF (Mediation Proportion)		49.7%			
Mediation Type		Partial			

Source: Primary Data Analysis, 2025; FL=Financial Literacy, DFI=Digital Financial Inclusion, EI=Entrepreneurial Intentions

4.8 Moderation Analysis

We further examined whether perceived ease of use of AI applications moderated the relationship between financial literacy and entrepreneurial self-efficacy, testing our third hypothesis. The interaction term achieved statistical significance with a path coefficient of 0.167 and p-value below 0.001, supporting our hypothesis. Simple slope analysis following Aiken and West (1991) revealed that the financial literacy to self-efficacy relationship strengthened substantially when perceived ease of use was high, with the slope increasing from 0.507 at low ease of use to 0.841 at high ease of use.

This moderation effect underscores the importance of user-friendly interface design in maximising intervention impact, consistent with TAM extensions emphasising facilitating conditions (Venkatesh et al., 2003). Financial knowledge gains translate into entrepreneurial confidence more effectively when the learning technology itself feels accessible and manageable. Conversely, when women struggle with technology interfaces despite acquiring financial knowledge, the confidence-building effect is attenuated. This finding reinforces our earlier observation regarding voice-based advantages for low-literacy populations and suggests that technology accessibility represents not merely a convenience factor but a substantive determinant of intervention effectiveness.

5. DISCUSSION

5.1 Interpretation of Key Findings

Our investigation yielded several findings warranting careful interpretation within the broader scholarly conversation regarding financial literacy, technology-enabled education, and women's entrepreneurship in developing economy contexts. The substantial improvements in financial literacy following AI-enabled intervention, with an overall effect size exceeding two standard deviations, surpass typical educational intervention effects reported in the literature. Kaiser and Menkhoff's (2017) review of financial education programmes found average effect sizes considerably more modest than what we observed. We attribute this enhanced impact to several factors characteristic of AI-enabled approaches.

Firstly, the adaptive learning algorithms adjusted content difficulty based on individual response patterns, ensuring that women with very limited baseline knowledge were not overwhelmed while those with greater existing capability were not bored (Holmes et al., 2019). Traditional classroom instruction must target some assumed average, inevitably leaving portions of learners inadequately served. Secondly, the privacy afforded by individual application engagement apparently encouraged learning behaviours that group settings might inhibit, consistent with research on help-seeking behaviour in educational contexts (Ryan & Pintrich, 1997). Multiple participants mentioned feeling comfortable asking basic questions that they would not have raised publicly. Thirdly, the voice-based interface enabled engagement amongst women for whom text-based materials would have been largely inaccessible (Aker & Mbiti, 2010).

The superior performance of voice-based delivery merits particular attention. While we anticipated some advantage based on literacy considerations, the magnitude of difference exceeded our expectations. Effect sizes for engagement measures approached and exceeded one standard deviation, indicating that interface modality fundamentally shapes user experience rather than merely providing marginal convenience. This finding contributes to the emerging literature on inclusive technology design, suggesting that voice-first architectures should be prioritised rather than treated as accommodations when serving populations with limited formal education (Heeks, 2018; Duncombe, 2016).

The mediation finding regarding digital financial inclusion offers novel theoretical contribution. Prior research has typically examined financial literacy and digital financial inclusion as parallel development objectives rather than sequentially linked phenomena (Grohmann et al., 2018). Our results suggest that financial literacy serves as a foundational capability enabling digital financial inclusion, which in turn reduces perceived barriers to entrepreneurship. This sequential understanding carries implications for programme design, suggesting that financial education should precede or accompany digital financial services rollout rather than assuming that service provision automatically generates inclusion.

5.2 Theoretical Contributions

This investigation extends existing theoretical frameworks in several ways. Regarding the Technology Acceptance Model (Davis, 1989), our findings suggest that the relative importance of perceived ease of use versus perceived usefulness may vary systematically across user populations. In Davis's original formulation and much subsequent

research conducted amongst educated professionals adopting workplace technologies, perceived usefulness typically demonstrates stronger influence than ease of use (Venkatesh & Davis, 2000). Our results show the reverse pattern, with ease of use exerting notably stronger influence on financial literacy acquisition than usefulness perceptions.

We interpret this reversal as reflecting the unique circumstances of populations with limited prior technology exposure and constrained literacy. For such users, fundamental accessibility concerns must be resolved before usefulness considerations become salient. A woman who struggles to navigate an application interface cannot evaluate whether its content would be useful even if she could access it. This suggests that TAM applications in inclusive development contexts should accord heightened attention to accessibility factors that educated user populations may take for granted, extending insights from Venkatesh et al. (2003) regarding facilitating conditions.

Regarding entrepreneurial intention theory, our findings highlight the mediating role of digital financial inclusion, a pathway not prominently featured in existing frameworks (Liñán & Chen, 2009). The Theory of Planned Behaviour emphasises attitudes, norms, and perceived behavioural control as intention determinants (Ajzen, 1991). Our results suggest that digital financial engagement functions as a mechanism through which perceived behavioural control is enhanced. Women who become comfortable transacting digitally, maintaining formal bank accounts, and accessing financial information online apparently perceive themselves as more capable of managing formal business operations. This digital capability dimension warrants integration into entrepreneurial intention models applied in contexts where digitalisation remains uneven.

5.3 Practical Implications

For policymakers designing inclusive development programmes aligned with the Viksit Bharat vision, our findings suggest several actionable directions. The National Rural Livelihoods Mission currently reaches approximately eighty-eight million rural women through its SHG platform (Ministry of Rural Development, 2024). Integrating vernacular AI financial literacy applications into this existing infrastructure could extend meaningful financial education at modest marginal cost. Our rough calculations suggest per-user costs of approximately two hundred fifty rupees for a four-week intervention, substantially below equivalent classroom training expenses estimated by Karlan and Valdivia (2011). The scalability of digital approaches addresses a persistent constraint limiting traditional capacity-building efforts.

Our findings regarding voice-based advantages carry implications for Digital India initiatives more broadly. Current digital literacy programmes and financial service applications predominantly employ text-based interfaces reflecting the educational backgrounds and assumptions of their urban, educated designers (Rao, 2019). For the several hundred million Indian adults with limited formal education (UNESCO, 2022), such interfaces create barriers that undermine inclusion objectives. Voice-first design principles, while requiring greater initial development investment, may yield substantially higher engagement and impact amongst intended beneficiaries.

For financial institutions seeking to expand rural customer bases, our results suggest that customer capability-building through free AI tools could simultaneously serve financial inclusion mandates and commercial objectives. Approximately two-thirds of our participants expressed willingness to open accounts with institutions providing the learning application, suggesting loyalty effects extending beyond the intervention itself. Furthermore, the improved financial behaviours associated with literacy gains, including better loan repayment discipline and more prudent borrowing documented by Drexler et al. (2014), could improve portfolio quality over time.

For technology developers, our findings validate specific design principles warranting broader adoption. Voice-first architecture enabling audio interaction without reading requirements should be default rather than optional for applications targeting rural populations. Vernacular language primacy using regional languages as primary interface rather than translated versions of English acknowledges linguistic realities (Heeks, 2018). Conversational simplicity through dialogue-based interactions mimicking natural conversation patterns reduces cognitive load. Cultural contextualisation using locally relevant examples and contexts enhances relatability and comprehension.

5.4 Limitations and Future Research

Several limitations qualify our findings and suggest directions for subsequent investigation. The cross-sectional design captured entrepreneurial intentions at a single post-intervention timepoint, leaving questions regarding actual behaviour actualisation unaddressed. Whether enhanced intentions translate into actual venture creation, and over what timeframe, requires longitudinal follow-up that we plan to conduct over the coming year. The intention-behaviour gap, while theoretically modest (Ajzen, 1991), varies across contexts in ways that warrant empirical examination (Shirokova et al., 2016).

Self-reported measures for several constructs, including digital financial inclusion and entrepreneurial intentions, introduce potential social desirability bias (Podsakoff et al., 2003). Participants aware of researchers' interests may have overstated intentions or usage behaviours. Future research would benefit from incorporating objective indicators such as actual account opening records, business registration filings, or transaction data where ethically obtainable.

The four-week intervention period, while demonstrating significant knowledge gains, represents insufficient time for behavioural entrenchment. Whether financial literacy gains persist over months and years following intervention cessation remains unknown, reflecting concerns raised by Fernandes et al. (2014) regarding intervention decay. Optimal intervention duration balancing impact with efficiency represents an empirical question warranting systematic investigation through varied-duration designs.

Sample characteristics limit generalisability beyond Tamil Nadu's relatively mature SHG ecosystem. The state's pioneering role in India's SHG movement has created institutional infrastructure, social norms regarding women's economic participation, and digital connectivity that may not obtain in states with newer or less developed SHG systems (Brody et al., 2017). Replication across varied Indian contexts would strengthen confidence in findings' broader applicability.

Finally, our focus on individual capability enhancement should not obscure structural constraints that individual knowledge cannot overcome (Kabeer, 2005). Patriarchal household dynamics restricting women's mobility, unequal labour divisions limiting available time, discriminatory lending practices, and inadequate market infrastructure all constrain entrepreneurial opportunity regardless of financial literacy levels. A comprehensive approach to women's entrepreneurship development must address structural barriers alongside individual capabilities, as emphasised in feminist economics perspectives (Mayoux, 2001).

6. CONCLUSION

This investigation examined how AI-powered financial literacy interventions influence entrepreneurial intentions amongst rural women participating in Self-Help Groups across Tamil Nadu. Our findings demonstrate that such interventions can substantially enhance financial literacy, with particularly strong effects when delivered through voice-based vernacular interfaces accommodating literacy constraints prevalent in rural contexts. Financial literacy gains translate into strengthened entrepreneurial intentions through dual pathways, directly through enhanced perceived capability and indirectly through increased digital financial inclusion that reduces perceived barriers to formal business operations.

These findings carry significance for India's developmental trajectory as articulated in the Viksit Bharat 2047 vision. Inclusive economic growth requires extending entrepreneurial opportunities to populations historically excluded from formal economic participation (World Bank, 2021). Technology-enabled interventions offer scalable, cost-effective mechanisms for building foundational capabilities amongst marginalised populations. However, realising this potential requires intentional design choices prioritising accessibility over assumptions reflecting developer rather than user characteristics.

The path toward developed nation status runs through rural communities where hundreds of millions of Indians reside. Their full economic participation cannot be assumed as automatic consequence of aggregate growth but must be actively enabled through targeted interventions respecting their circumstances, languages, and capabilities (Sen, 1999). AI-enabled financial literacy represents one promising element in a necessarily multifaceted approach to inclusive development. Our findings offer modest but hopefully useful evidence regarding how such interventions might be designed and implemented to maximise impact amongst those who stand to benefit most.

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