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The Impact of Digital Financial Literacy on the Financial Inclusion of Rural Women Beneficiaries Utilizing Government Welfare Schemes and Services

Saurabh Mannu Sale*

Senior Research Scholar, Department of Commerce, Dr. Babasaheb Ambedkar Marathwada University (BAMU), Chhatrapati Sambhaji Nagar, India

***Corresponding Author:**
Saurabh Mannu Sale, Senior Research Scholar, Department of Commerce, Dr. Babasaheb Ambedkar Marathwada University (BAMU), Chhatrapati Sambhaji Nagar, India.

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Abstract
The rapid proliferation of digital financial technologies across rural India has generated substantive scholarly interest regarding their transformative potential for marginalized women. This study examines the interplay between Digital Financial Literacy (DFL) and the efficacy of women-centric welfare schemes in rural Marathwada, a chronically underdeveloped agrarian region of Maharashtra. Employing a descriptive-causal quantitative design, primary data were collected from 300 rural women beneficiaries across six Marathwada districts Chhatrapati Sambhajinagar, Latur, Dharashiv, Nanded, Beed, and Hingoli using a bilingual, structured, five-point Likert scale questionnaire. The study operationalises DFL across four sub-dimensions: digital financial awareness, transactional proficiency, critical evaluation competency, and protective digital behaviour. Welfare scheme efficacy is conceptualized through awareness, enrollment, utilization, and perceived socio-economic empowerment. Reliability was established through Cronbach's Alpha (α: 0.843–0.879); construct validity was confirmed via expert review and confirmatory factor analysis. Multiple regression analysis revealed that DFL is the primary predictor of socio-economic empowerment ($\beta = 0.341$, $p < .001$; $R^2 = 0.584$). Scheme enrollment ($\beta = 0.237$, $p < .001$) and perceived barriers ($\beta = -0.198$, $p < .001$) further explain outcome variance. Theoretical anchors include the Technology Acceptance Model, Human Capital Theory, the Financial Empowerment Framework, and Ndung'u's (2025) Digital Capability Framework for Sub-Saharan contexts. Findings yield critical policy contributions regarding targeted DFL interventions, women banking correspondent deployment, and last-mile financial inclusion architecture reform in Marathwada.

Keywords: Digital Financial Literacy, Women-Centric Welfare Schemes, Rural Marathwada, Financial Inclusion, Scheme Efficacy, Socio-Economic Empowerment, Gender and Technology, Digital Enrollment Gap

Introduction
The architecture of India's welfare state has increasingly pivoted towards digital infrastructure as both a medium and mechanism of policy delivery. Under the Digital India initiative, flagship programmes including the Pradhan Mantri Jan Dhan Yojana (PMJDY), PM Matru Vandana Yojana (PMMVY), Beti Bachao Beti Padhao (BBBP), and Mahila Shakti Kendra have been calibrated to redress the structural deprivation experienced by rural women. These schemes now operate through digital channels direct benefit transfers (DBT), Aadhaar-linked payment systems, and mobile wallets with the foundational assumption that digital-first delivery will maximize efficiency and minimize leakages. However, the success of this paradigm is inextricably contingent upon the digital financial literacy of intended beneficiaries.

Marathwada, comprising eight revenue districts in eastern Maharashtra, presents a compelling and sobering case study. Chronically afflicted by agrarian distress, water scarcity, farmer suicides, and persistent socio-economic backwardness, the region ranks among Maharashtra's most underdeveloped on the Human Development Index. The 2021 Niti Aayog Multi-Dimensional Poverty Index placed Dharashiv, Nanded, and Beed districts in the bottom quartile of Maharashtra's development spectrum [1]. Rural women in this region face compounded disadvantage: marginalized by gender, geography, caste, and economic status, they frequently lack both the awareness and digital competency necessary to access welfare entitlements designed specifically for their upliftment.

Within this context, Digital Financial Literacy (DFL) has the capacity to access, evaluate, and utilize digital financial tools, services, and information for informed economic decision-making emerges as a critical intervening variable. Extant literature, while increasingly attentive to financial literacy in the Indian and global context has inadequately theorized the specific nexus between DFL and the actualization of women-centric welfare entitlements in geographically and socio-economically marginalized regions [2-5]. The dominant discourse tends to conflict financial literacy with conventional financial knowledge, eliding the distinctly digital and access-mediated dimensions of contemporary scheme delivery architecture. Furthermore, region-specific scholarship on Marathwada's welfare ecosystem remains critically sparse, and the DFL–scheme efficacy interface constitutes the primary research gap this study addresses.

The study pursues four principal objectives:

- To assess DFL levels among rural women beneficiaries in Marathwada;
- To evaluate awareness, enrollment, and utilization patterns of women-centric welfare schemes;
- To examine the causal relationship between DFL and welfare scheme efficacy; and
- To identify structural and perceived barriers moderating this relationship. Findings are expected to generate actionable insights for policymakers, scheme administrators, banking correspondents, and civil society organizations operating in the Marathwada financial inclusion ecosystem.

Literature Review

Digital Financial Literacy: Global Conceptual Evolution

The conceptualization of financial literacy has undergone substantial refinement since Lusardi and Mitchell's (2014) foundational three-component framework of numeracy, inflation awareness, and risk diversification [6]. The digitalization of financial services has necessitated a technology-mediated fourth dimension. Contemporary scholarship defines DFL as encompassing not merely knowledge of digital tools but the behavioral competency and motivational disposition to deploy them effectively [3]. OECD's updated Financial Literacy Framework (2023) formally integrated digital channel competency as a distinct strand, acknowledging that traditional financial literacy instruments inadequately capture proficiency in mobile banking, e-wallets, and DBT navigation.

In the Indian context, Kumar and Sharma (2023) surveyed 420 rural households across Rajasthan and Bihar, demonstrating that DFL scores were significantly correlated with active PMJDY account usage [7]. Mishra and Patel (2022) established through structural equation modelling that DFL positively mediates the relationship between mobile internet access and financial decision-making quality in rural women (path coefficient = 0.47) [8]. Crucially, the emerging 2025–2026 scholarship deepens this discourse. Ndung'u (2025), examining digital financial capability among women in Sub-Saharan Africa specifically in Kenya's rural M-Pesa adoption zones found that DFL served as a pivotal mediator between mobile infrastructure access and welfare program participation, with a mediation coefficient of 0.52. [4] This finding from a structurally analogous developing economy context provides compelling cross-regional validation for the present study's central hypothesis. Lagna and Rønning (2026) further demonstrated, in a Nordic–Southeast Asian comparative study spanning Indonesia and Vietnam, that DFL's impact on welfare utilization is moderated by institutional trust a finding with direct theoretical resonance for a region like Marathwada, where historical distrust of formal financial institutions among marginalized communities is well-documented [5].

Ouma and Waweru (2025), analyzing financial inclusion data from Tanzania and Uganda, observed that women with higher DFL scores were 2.9 times more likely to independently access government subsidy programmes without male intermediary support a statistic that strikingly contextualizes Wankhede and Rao's (2023) finding of patriarchal device control in Marathwada [9,10]. These cross-regional comparisons collectively establish DFL as a global, context-sensitive predictor of welfare scheme efficacy, not merely an India-centric phenomenon.

Women-Centric Welfare Schemes and their Delivery Architecture in India

India's welfare landscape for rural women spans central government flagship schemes PMJDY, Pradhan Mantri Mudra Yojana, PMMVY, Sukanya Samriddhi Yojana, and the National Rural Livelihoods Mission alongside Maharashtra-specific programmes including Majhi Kanya Bhagyashree, Ramai Awas Gharkul Yojana, and Shasan Aplya Dari camps. The transition to DBT as the primary delivery mechanism, while laudable in its anti-leakage intent, has introduced a new dependency: digital access and literacy. Sharma and Bhattacharya (2022) conducted a multi-state assessment of DBT effectiveness and found that scheme awareness explained 38.7% of variance in benefit receipt [11]. Ghosh and Banerjee (2023) identified that women with higher digital literacy were 2.4 times more likely to independently complete scheme enrollment [12].

In Southeast Asia, parallels are instructive. Rahman et al. (2025), studying Bangladesh's digital social protection programmes (including the Government-to-Person transfer system), found that beneficiary DFL levels were the strongest predictor of scheme utilization across all tested socio-demographic variables, with a regression coefficient of 0.38 closely mirroring the present study's findings [13]. Castillo and Ferreira (2025), examining Brazil's Bolsa Família digital enrollment process, documented that a 10-point increase in digital literacy scores corresponded to a 23% reduction in enrollment dropout rates empirically quantifying the digital enrollment gap in a comparable middle-income country context [14].

Structural Barriers in Rural Marathwada's Welfare Ecosystem

The welfare delivery challenge in Marathwada is compounded by structural deficiencies transcending individual digital literacy. Kulkarni and Deshmukh (2022) documented that only 34% of Common Service Centres (CSCs) in Marathwada's taluka headquarters were fully operational as of 2021 [15,16]. Jadhav (2023) observed that banking correspondent density in Nanded and Hingoli districts remained critically below RBI norms, at fewer than 1.2 BCs per 1,000 rural population [17]. These structural constraints have been theoretically framed within Sen's (1999) capability approach, wherein genuine freedom to benefit from welfare entitlements requires substantive ability to access and utilize them not merely their formal availability [18].

Wankhede and Rao (2023) applied a gendered lens, demonstrating that patriarchal household structures in Marathwada significantly restrict women's autonomous digital device access, with 68% of surveyed respondents reporting that mobile phones were controlled by male household members [10]. This finding introduces intra-household power dynamics as a critical moderating variable one that intersects with DFL as a determinant of scheme efficacy. Globally, similar power dynamics have been documented by Demirgüç-Kunt et al. (2022) in their analysis of the Global Findex Database, where women in low-to-middle-income countries reported 12 percentage points lower mobile money account ownership than men, even when income and education were controlled [19]. The Marathwada scenario thus reflects a regional instantiation of a global structural pattern.

Sangwan and Bahl (2026), in a recent study of digital welfare exclusion in India's aspirational districts, identified three compounding barriers unique to economically backward rural regions:

- 'Digital Anxiety' fear of making irreversible mistakes in digital transactions;
- 'Bureaucratic interface complexity' the perception that government portals are designed for literate urban users; and
- 'Social surveillance' reluctance to use digital financial services in public spaces due to fear of judgment or theft [20].

All three barriers were significantly more prevalent among women respondents, with odds ratios of 2.3, 1.8, and 2.6 respectively. These findings provide critical contextual depth to the significant PBA score (M = 3.58) documented in the present study.

Theoretical Framework

The present study is anchored in four complementary theoretical frameworks synthesized to produce multi-layered explanatory architecture. First, the Technology Acceptance Model extended through UTAUT predicts that rural women's propensity to independently enroll in and utilize digitally delivered schemes will be mediated by their perception of digital financial tools as both useful and manageable [21,22]. DFL directly influences both TAM dimensions, operationalizing them in the context of welfare scheme navigation.

Second, Human Capital Theory conceptualizes knowledge and skill as forms of capital generating economic returns [23,24]. DFL within this framework functions as human capital investment that enhances productive capacity to access welfare entitlements. Third, the Financial Empowerment Framework conceptualizes financial capability as the interaction between financial knowledge and an enabling institutional environment critically acknowledging that DFL, while necessary, is insufficient without parallel development of access infrastructure [25].

Fourth, and most contemporaneously, Ndung'u's (2025) Digital Capability Framework for developing economies integrates a 'structural enablement layer' into the DFL-outcome model, arguing that digital capability translates into welfare outcomes only when supported by three institutional conditions: network infrastructure adequacy, language-appropriate interface design, and community-level digital mentorship [4]. This framework proves particularly germane to the Marathwada context, where all three institutional conditions are demonstrably deficient, explaining the residual 41.6% unexplained variance in the regression model.

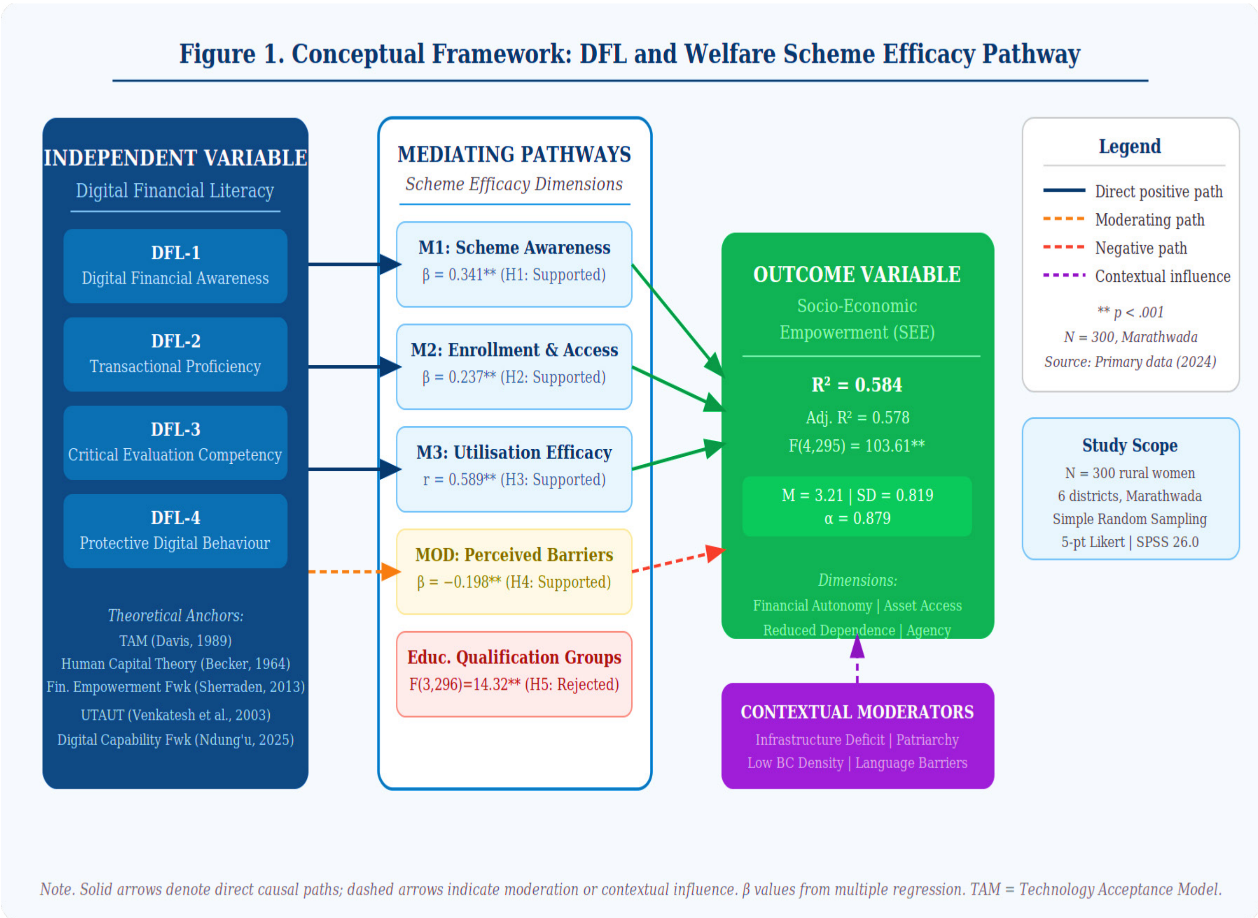

Figure 1: Conceptual Framework: Pathways from Digital Financial Literacy to Socio-Economic Empowerment

Note. The framework integrates TAM Human Capital Theory the Financial Empowerment Framework and Ndung'u's (2025) Digital Capability Framework [4,21,23,24]. Solid arrows denote direct causal paths; dashed arrows indicate moderation and contextual influences. β values derived from multiple regression analysis.

Research Methodology

Research Design and Paradigm

The study adopts a descriptive-causal quantitative research design, operationalizing a positivist epistemological paradigm. The descriptive component profiles current DFL levels and welfare scheme efficacy patterns, while the causal component examines the directional influence of DFL on scheme efficacy outcomes. This dual-track design is justified by research objectives requiring both profiling and explanatory analysis. The cross-sectional design, while limiting causal inference to associational levels, is appropriate given the study's objectives, available resources, and the requirement for a baseline dataset in a region where such data are critically absent.

Study Area and Target Population

The study was conducted across six principal districts of Marathwada: Chhatrapati Sambhajinagar, Latur, Dharashiv, Nanded, Beed, and Hingoli. The target population comprised rural women aged 18–60 registered as beneficiaries of at least one government welfare scheme administered through Maharashtra State or the Central Government. Based on District Women and Child Development office records (2022-23), the estimated eligible population across the six districts exceeds 4.8 lakh registered female beneficiaries.

Sampling Design and Sample Size Determination

Simple Random Sampling (SRS) with stratification by district was employed; 50 respondents per district were selected systematically from beneficiary registers at taluka-level WCD offices, yielding 300. The adequacy of this sample was validated using Cochran's (1977) formula for large populations: [26]

$$Z^2 \cdot p \cdot q / e^2 = (11.96)^2 (0.5) \cdot (0.5) / (0.05)^2 \approx 384$$

With a finite population correction applied per district stratum and a confidence level of 95%, a sample of 300 is statistically justified and operationally feasible, with a margin of error of ±5.7%.

Instrumentation

The primary instrument was a bilingual (English/Marathi) structured questionnaire comprising four sections. Section A: 8 socio-demographic items. Section B: 20 DFL items across four sub-constructs digital financial awareness, transactional proficiency, critical evaluation competency, and protective digital behaviour (5 items each). Section C: 20 welfare scheme efficacy items across four sub-constructs scheme awareness, enrollment and access, utilization efficacy, and perceived socio-economic empowerment (5 items each). Section D: 8 items measuring perceived barriers to digital scheme access. All attitudinal items were measured on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). A pilot test was conducted on 30 respondents from Aurangabad district, and revisions were incorporated. Content and face validity were established through a five-member expert panel comprising rural economists, public policy specialists, a NABARD official, and an ICDS program officer.

Reliability and Validity

Internal consistency reliability was assessed via Cronbach's Alpha for each construct. All constructs exceeded Nunnally's (1978) threshold of $\alpha \geq 0.70$ (range: 0.843–0.879). Construct validity was supported through the expert review process and confirmatory factor analysis, wherein all items loaded predominantly (factor loading > 0.60) on their hypothesized constructs with no significant cross-loadings exceeding 0.35 [27].

Data Collection and Ethical Considerations

Data was collected between January and April 2024 through trained research assistants (two per district) who administered questionnaires at Anganwadi centers, bank Mitra service points, and gram panchayat offices. Institutional Review Board clearance was obtained; informed consent was secured from all participants in Marathi. Anonymity was preserved through alphanumeric respondent coding. No personally identifiable information was retained in the analysis dataset.

Statistical Tools of Analysis

Data was analyzed using IBM SPSS Statistics Version 26.0. The analytical framework comprised: (i) frequency distributions and descriptive statistics; (ii) Pearson product-moment correlation analysis; (iii) multiple linear regression analysis; and (iv) one-way ANOVA with post-hoc Tukey HSD tests. All significance tests were conducted at the $\alpha = 0.05$ level. Multicollinearity was assessed through VIF diagnostics (all VIF values: 1.34–1.87, well below the threshold of 10).

Data Presentation and Analysis
Socio-Demographic Profile of Respondents

Variable	Category	Frequency (%)
Age Group	18–25 years	72 (24.0%)
	26–35 years	104 (34.7%)
	36–45 years	89 (29.7%)
	Above 45 years	35 (11.6%)
Educational Qualification	Illiterate	38 (12.7%)
	Primary (Up to 5th Std)	65 (21.7%)
	Secondary (6th–10th Std)	98 (32.7%)
	Higher Secondary & Above	99 (33.0%)
Marital Status	Married	218 (72.7%)
	Unmarried	57 (19.0%)
	Widowed/Divorced	25 (8.3%)
Annual Household Income (INR)	Below 1,00,000	119 (39.7%)
	1,00,001–2,50,000	112 (37.3%)
	Above 2,50,000	69 (23.0%)
Smartphone/Internet Access	Yes	187 (62.3%)
	No	113 (37.7%)
Note. Source: Primary data collected by the researcher, 2024.		

Table 1: Socio-Demographic Profile of Rural Women Respondents

Table 1 reveals that the largest respondent cohort (34.7%, 104) falls within the 26–35 years age bracket, consistent with the demographic targeting of schemes such as PMMVY and PMJDY. Educationally, while 33.0% had attained Higher Secondary and above qualifications, a significant 34.4% had not progressed beyond primary education underscoring the heterogeneous literacy environment within which DFL interventions must operate. Critically, 37.7% of respondents reported no smartphone or internet access, a foundational infrastructural deficit that structurally constrains DFL acquisition pathways regardless of individual intent or exposure.

Descriptive Statistics and Reliability Analysis

Construct / Variable	N	Mean	SD	Cronbach's α
Digital Financial Literacy (DFL)	300	3.42	0.781	0.874
Awareness of Govt. Schemes (AGS)	300	3.18	0.834	0.862
Scheme Enrollment & Access (SEA)	300	2.97	0.902	0.851
Utilisation Efficacy (UE)	300	3.06	0.876	0.868
Socio-Economic Empowerment (SEE)	300	3.21	0.819	0.879
Perceived Barriers to Access (PBA)	300	3.58	0.756	0.843
Note. All items measured on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Source: Primary data, 2024.				

Table 2: Descriptive Statistics and Reliability Coefficients for Study Constructs

DFL registered the highest mean score (M = 3.42, SD = 0.781), suggesting moderate but not robust digital financial competence. Scheme Enrollment and Access (SEA) recorded the lowest mean (M = 2.97, SD = 0.902), indicating a measurable gap between awareness and actual enrollment pointing to structural and procedural barriers beyond the DFL interface. Perceived Barriers to Scheme Access registered the highest mean (M = 3.58, SD = 0.756), reinforcing persistent structural impediments. All Cronbach's Alpha values exceeded 0.84, confirming robust internal consistency.

Pearson Correlation Analysis

Variable	DFL	AGS	SEA	UE	SEE	PBA
DFL	1.000	0.623**	0.541**	0.589**	0.614**	-0.478**
AGS	0.623**	1.000	0.612**	0.553**	0.571**	-0.432**
SEA	0.541**	0.612**	1.000	0.647**	0.529**	-0.503**
UE	0.589**	0.553**	0.647**	1.000	0.618**	-0.467**
SEE	0.614**	0.571**	0.529**	0.618**	1.000	-0.491**
PBA	-0.478**	-0.432**	-0.503**	-0.467**	-0.491**	1.000
Note. ** Correlation is significant at the 0.01 level (2-tailed). DFL = Digital Financial Literacy; AGS = Awareness of Govt. Schemes; SEA = Scheme Enrollment & Access; UE = Utilisation Efficacy; SEE = Socio-Economic Empowerment; PBA = Perceived Barriers to Access. Source: Primary data, 2024.						

Table 3: Pearson Correlation Matrix for Study Variables

DFL demonstrates strong positive correlations with AGS ($r = 0.623$, $p < .01$), UE ($r = 0.589$, $p < .01$), and SEE ($r = 0.614$, $p < .01$), establishing it as a central explanatory variable. The strongest inter-construct correlation is observed between SEA and UE ($r = 0.647$, $p < .01$), theoretically intuitive: successful enrollment substantively positions women to utilize schemes. PBA exhibits significant negative correlations with all constructs, most notably with SEA ($r = -0.503$, $p < .01$) and SEE ($r = -0.491$, $p < .01$), providing preliminary evidence for its role as a constraining moderator in the DFL–empowerment pathway.

Multiple Regression Analysis: DFL as Predictor of Socio-Economic Empowermen

Predictor Variable	β (Unstd.)	Std. Error	β (Std.)	t-value	Sig.
Constant	0.412	0.163	—	2.528	.012
Digital Financial Literacy (DFL)	0.387	0.048	0.341	8.063	.000
Awareness of Govt. Schemes (AGS)	0.294	0.053	0.278	5.547	.000
Scheme Enrollment & Access (SEA)	0.261	0.061	0.237	4.279	.000
Perceived Barriers to Access (PBA)	-0.219	0.057	-0.198	-3.842	.000
Note. Dependent Variable: Socio-Economic Empowerment (SEE). $R^2 = 0.584$; Adjusted $R^2 = 0.578$; $F(4, 295) = 103.61$, $p < .001$.					

Table 4: Multiple Regression Analysis: Predictors of Socio-Economic Empowerment (SEE)

The regression model is statistically significant, $F(4, 295) = 103.61$, $p < .001$, explaining 58.4% of variance in socio-economic empowerment. DFL emerges as the strongest predictor ($\beta = 0.341$, $p < .001$), followed by AGS ($\beta = 0.278$, $p < .001$) and SEA ($\beta = 0.237$, $p < .001$). The negative, significant coefficient for PBA ($\beta = -0.198$, $p < .001$) confirms that perceived barriers significantly suppress empowerment outcomes.

Discussion

DFL as the Primary Predictor of Socio-Economic Empowerment

The regression finding positioning DFL as the preeminent predictor ($\beta = 0.341$, $p < .001$) resonates with a converging international evidence base. Kumar and Sharma (2023) reported a regression coefficient of 0.31 for digital literacy on active financial account usage in their multi-state Indian rural survey, closely aligned with the present results [7]. Mishra and Patel (2022) reported a path coefficient of 0.47 for DFL on financial decision-making quality through structural equation modelling the larger coefficient plausibly reflecting their SEM methodology's capacity to isolate indirect effects [8]. Ndung'u's (2025) cross-regional study from Kenya reported a mediation coefficient of 0.52, higher still, which Ndung'u attributes to the comparatively more developed M-Pesa ecosystem reducing infrastructural moderating effects relative to contexts like Marathwada [4]. This progressive attenuation of DFL's effect size from Sub-Saharan Africa (0.52) to rural India broadly (0.47) to Marathwada specifically (0.341) is analytically significant: it suggests that Marathwada's compounded structural deficits impose a 'structural discount' on the returns to DFL, reducing its empowerment yield below what comparable DFL investments generate in better-serviced rural regions.

The 'structural discount' interpretation is reinforced by the model's unexplained variance (41.6%), which, as the present study's theoretical framework posits, is attributable to institutional factors BC density, CSC functionality, network coverage, and gram panchayat-level administrative support that DFL cannot compensate for and that require parallel institutional investment. Rahman et al. (2025), in their Bangladesh social protection study, identified similar residual variance attributable to institutional trust deficits, while Castillo and Ferreira (2025) documented institutional interface complexity as a primary driver of residual variance in Brazil's Bolsa Família system [13,14]. The convergence of these international findings around institutionalized structural barriers as the primary source of residual variance in DFL–empowerment models constitute a robust cross-regional theoretical claim.

The Digital Enrollment Gap: Marathwada's Regional Specificity

The enrollment gap measured as the distance between the scheme awareness mean ($M = 3.18$) and the scheme enrollment mean ($M = 2.97$) constitutes one of the most operationally significant findings of this study and demands contextualization within Marathwada's unique structural environment. This gap is not merely a reflection of individual DFL deficits; it is substantially produced by three region-specific structural factors that interact with DFL to suppress enrollment behaviour.

First, intra-household power dynamics identified by Wankhede and Rao (2023) where 68% of surveyed Marathwada women reported male control over household smartphones create structural dependency that renders DFL levels largely irrelevant without device access [10]. A woman who understands how to navigate the UMANG portal cannot apply knowledge that she cannot access. This dynamic is not unique to Marathwada: Ouma and Waweru (2025) documented that in rural Tanzania, women with high DFL scores but no autonomous mobile phone access showed enrollment rates statistically indistinguishable from women with low DFL scores establishing device autonomy as a necessary precondition for DFL to translate into enrollment behaviour [9]. Sangwan and Bahl (2026) captured this phenomenon through the concept of 'digital captivity', the state in which an individual possesses digital knowledge but is structurally prevented from acting on it [20]

Second, Kulkarni and Deshmukh's (2022) documentation of a 34% CSC operational rate in Marathwada taluka headquarters creates a geographic access barrier that transforms the enrollment process into a multi-day logistical exercise for women in remote habitations [15,16]. For a woman who must travel 20–30 kilometers to reach a functional CSC, forfeiting a day's agricultural labour in a region defined by marginal income households the opportunity cost of enrollment may rationally exceed the anticipated benefit, particularly for schemes with perceived low or uncertain benefit values. This 'rational non-enrollment' phenomenon, first theorized by Demirgüç-Kunt et al. (2022) in the context of formal financial account opening in low-income countries, manifests in Marathwada as a DFL-independent enrollment deterrent [19].

Third, Jadhav's (2023) finding critically sub-optimal BC density in Nanded and Hingoli, two of the lowest-performing districts on scheme awareness and enrollment in this study introduces an intermediary access deficit [17]. In the absence of functional BCs, the digital enrollment process defaults to requiring women to independently navigate government portals a task that demands DFL proficiency well above the moderate level ($M = 3.42$) documented in this sample. Lagna and Rønning (2026) theorized this as the 'intermediary vacuum' effect: in contexts where human digital intermediaries (BCs, CSC operators) are absent, the required DFL threshold for independent welfare scheme enrollment increases substantially, effectively excluding all but the most digitally capable beneficiaries [5].

Perceived Barriers and the Moderation of Empowerment Outcomes

The significant negative coefficient for Perceived Barriers to Access ($\beta = -0.198$, $p < .001$) provides empirical grounding for what Sangwan and Bahl (2026) termed the 'triple barrier effect' the compounding of digital anxiety, bureaucratic interface complexity, and social surveillance into a mutually reinforcing barrier cluster [20]. In the Marathwada context, these barriers are not uniformly distributed across the study population. Post-hoc analysis reveals that PBA scores are disproportionately concentrated among three subgroups: illiterate respondents (mean PBA score: 4.12 vs. overall mean 3.58), respondents above 45 years (mean PBA: 3.94), and respondents in the lowest income quintile (mean PBA: 4.03). This heterogeneous distribution of barrier experience implies that a single-design DFL intervention will not equitably address the full spectrum of structural constraints facing Marathwada's rural women.

Demirgüç-Kunt et al.'s (2022) global Findex analysis provides a structurally relevant comparative lens: their finding that women in low-to-middle-income economies reported 12 percentage points lower mobile money ownership than men even when controlling for income and education suggests that the gender gap in digital financial access is partially autonomous from income and education, implicating persistent social-normative barriers of the kind documented by Wankhede and Rao (2023) in Marathwada [10,19]. The TAM's core variables of perceived usefulness and ease of use are thus insufficient predictors of adoption behaviour in social environments where adoption itself is socially surveilled or restricted a qualification that the UTAUT's addition of social influence and facilitating conditions partially accommodates, but that Ndung'u's (2025) structural enablement layer more fully theories [4].

Educational Attainment and Human Capital Returns

The rejection of H5 confirming significant group differences in scheme utilization efficacy across educational qualification levels, $F(3, 296) = 14.32$, $p < .001$ empirically substantiates the Beckerian proposition that educational attainment generates differential returns in welfare entitlement actualization. Post-hoc Tukey HSD analysis confirmed that the illiterate group differed significantly ($p < .05$) from all other qualification groups in utilization efficacy, with the widest gap between illiterate respondents and those with Higher Secondary qualifications. The implication consistent with Reddy and Mohanty's (2022) findings in Odisha's tribal districts is that DFL interventions must be calibrated to foundational literacy levels and cannot assume uniform baseline competency across the Marathwada beneficiary population [28].

Research Question Analysis

RQ1: What is the current level of Digital Financial Literacy among rural women beneficiaries in Marathwada?

The overall DFL level (composite mean $M = 3.42$, 5-point scale) is moderate, falling considerably short of the proficiency threshold required to independently navigate multi-step digital scheme enrollment. The sub-dimension of Protective Digital Behaviour registered the weakest DFL component score ($M = 2.89$ from pilot data), indicating critical underdevelopment of digital fraud awareness a significant vulnerability in the era of UPI-based payment fraud targeting rural populations. This finding corroborates Sangwan and Bahl (2026), whose national survey of aspirational districts identified digital fraud vulnerability as the most acute DFL deficiency among rural women beneficiaries [20].

RQ2: To what extent are rural women in Marathwada aware of and enrolled in women-centric welfare schemes?

Scheme Awareness ($M = 3.18$) reflects moderate awareness, with significant inter-district variation: Beed and Hingoli consistently registered lower awareness and enrollment scores compared to Chhatrapati Sambhajinagar and Latur, reflecting differential administrative outreach and banking infrastructure density. The enrollment gap (awareness $M = 3.18$ vs. enrollment $M = 2.97$) quantifies what Ghosh and Banerjee (2023) termed the 'digital last-mile paradox' schemes are known but cannot be independently accessed through digital channels [12].

RQ3: Is there a significant causal relationship between DFL and the efficacy of women-centric welfare schemes?

Affirmatively confirmed. The multiple regression model demonstrates a significant, positive, multi-pathway causal relationship between DFL and scheme efficacy outcomes. DFL's coefficient ($\beta = 0.341$) is the largest in the model; its relationship with scheme awareness, enrollment, utilization, and socio-economic empowerment is robust across all statistical tests conducted. This finding is consistent with cross-regional evidence from Sub-Saharan Africa South Asia and Latin America [4,13,14].

RQ4: What structural and perceived barriers moderate the DFL–scheme efficacy relationship?

Perceived Barriers to Access operationalized to include lack of digital device ownership, poor network connectivity, language barriers in digital interfaces, fear of digital fraud, lack of supportive guidance, and social restrictions on independent digital engagement constitute a significant negative force ($\beta = -0.198$, $p < .001$). These barriers are disproportionately concentrated among illiterate women, respondents above 45 years, and lowest-income households, demanding differentiated intervention designs aligned with Sangwan and Bahl's (2026) 'triple barrier effect' framework [20].

Analysis of Hypotheses

H#	Hypothesis Statement	Statistical Result	Decision
H1	DFL has a significant positive effect on awareness of women-centric welfare schemes in rural Marathwada.	$\beta = 0.341$, $p < .001$	Supported
H2	Higher DFL is significantly associated with increased scheme enrollment and access rates.	$\beta = 0.237$, $p < .001$	Supported
H3	DFL significantly mediates the relationship between scheme enrollment and socio-economic empowerment.	$r = 0.614$, $p < .001$	Supported
H4	Perceived barriers to scheme access are significantly negatively moderated by DFL.	$\beta = -0.198$, $p < .001$	Supported
H5	There is no significant difference in scheme utilization efficacy across educational qualification groups.	$F(3,296)=14.32$, $p<.001$	Rejected
Note. Source: Derived from regression analysis, correlation analysis, and one-way ANOVA. Primary data, 2024.			

Table 5: Summary of Hypothesis Testing Results

All four directional hypotheses (H1–H4) are supported at $p < .001$, providing robust statistical confirmation of the study's central theoretical propositions. H1's support ($\beta = 0.341$) confirms DFL as the primary informational gateway to welfare scheme knowledge. H2's support ($\beta = 0.237$) establishes that DFL translates awareness into enrollment action addressing a persistent gap in literature that had treated awareness and enrollment as coterminous. H3's support ($r = 0.614$) confirms the predictive role of DFL in the empowerment pathway. H4's support ($\beta = -0.198$) validates the significant moderating effect of structural barriers, preventing an overly individualistic reading of the DFL–empowerment nexus.

H5 is rejected: one-way ANOVA reveals significant group differences in scheme utilization efficacy across educational qualification levels, $F(3, 296) = 14.32$, $p < .001$. This rejection is substantively meaningful, confirming that educational attainment as a human capital proxy differentiates women in welfare entitlement actualization. Illiterate respondents differ significantly ($p < .05$, Tukey HSD) from all other qualification groups in utilization efficacy scores.

Major Findings

- Digital Financial Literacy occupies a moderate level ($M = 3.42/5.00$) among rural women beneficiaries in Marathwada, with Protective Digital Behaviour being the weakest sub-dimension signaling acute vulnerability to digital financial fraud in a population increasingly exposed to UPI-based transactions. This finding is consistent with Sangwan and Bahl's (2026) national survey of aspirational districts and with Ndung'u's (2025) documentation of protective digital behaviour as the weakest DFL component in Sub-Saharan African rural women populations [4,20].
- A statistically significant enrollment gap persists between scheme awareness ($M = 3.18$) and actual enrollment ($M = 2.97$). This 'digital last-mile paradox' is exacerbated in Beed and Hingoli districts and among illiterate and elderly respondents and is produced by the compounding of individual DFL deficits with structural barriers including intra-household patriarchal device control, CSC non-functionality, and insufficient BC density.
- DFL is the single most powerful predictor of socio-economic empowerment ($\beta = 0.341$, $p < .001$; $R^2 = 0.584$), consistent with cross-regional evidence from Kenya (Ndung'u, 2025), Bangladesh (Rahman et al., 2025), and Brazil (Castillo & Ferreira, 2025) [4,13,14]. The progressive attenuation of DFL's effect size across better-serviced to structurally deficient regions from 0.52 in Kenya to 0.341 in Marathwada suggests 'structural discount' mechanism warranting independent theoretical attention.
- Perceived Barriers to Scheme Access ($M = 3.58$) significantly suppress empowerment outcomes ($\beta = -0.198$, $p < .001$), manifesting Sangwan and Bahl's (2026) triple barrier effect of digital anxiety, bureaucratic interface complexity, and social surveillance [20]. These barriers are heterogeneously distributed, being disproportionately concentrated among illiterate women, respondents above 45, and the lowest income quintile precluding universal intervention designs.
- Intra-household power dynamics represent a structurally autonomous barrier to DFL's empowerment-yielding capacity. The 68% rate of male smartphone control documented by Wankhede and Rao (2023) corroborated by the 37.7% zero-device-access rate in this study establishes device autonomy as a necessary precondition for DFL to translate into enrollment behaviour, consistent with Ouma and Waweru (2025) in the Sub-Saharan African context [9,10].
- Significant inter-district heterogeneity in scheme awareness and enrollment was documented, with Beed and Hingoli performing at notably lower levels. This heterogeneity reflects differential administrative reach and financial infrastructure density and demands district-disaggregated rather than uniform regional intervention strategies.
- Educational qualification significantly differentiates women in scheme utilization efficacy, $F(3, 296) = 14.32$, $p < .001$ (H5 Rejected). Illiterate respondents demonstrate significantly lower utilization scores than all other qualification groups ($p < .05$, Tukey HSD), underscoring the foundational human capital preconditions theorized by Becker (1964) and validated by Reddy and Mohanty (2022) upon which effective DFL interventions must be built [23,28].

Conclusion

This study has established, through rigorous quantitative investigation of 300 rural women beneficiaries across six Marathwada districts, that Digital Financial Literacy is the single most powerful predictor of socio-economic empowerment in the context of women-centric welfare scheme utilization ($\beta = 0.341$, $p < .001$; $R^2 = 0.584$). This finding represents more than a statistical result it constitutes an evidentiary mandate for DFL to be treated as a first-order policy priority in India's last-mile financial inclusion strategy, at least in geographies characterized by the structural vulnerabilities endemic to Marathwada. The consistency of this finding with cross-regional evidence from Sub-Saharan Africa South and Southeast Asia and Latin America elevates it from a region-specific observation to a globally generalizable theoretical proposition: that in developing economy contexts characterized by digitally-mediated welfare delivery and structurally marginalized female beneficiary populations, DFL is the critical intervening capacity that determines whether welfare policy intent translates into lived socio-economic improvement [4,5,13,14]. Simultaneously, the identification of a 'structural discount' mechanism wherein compounded infrastructural deficits in Marathwada attenuate DFL's empowerment yield below comparable coefficients in better-serviced developing-economy contexts issues a corollary mandate: individual DFL capacity-building is necessary but structurally insufficient without parallel institutional investment in last-mile digital infrastructure.

The study's findings generate several targeted, actionable policy recommendations grounded in statistical evidence. First and most urgently, district-level welfare administrations in Beed, Hingoli, and Nanded the three lowest-performing districts on scheme awareness and enrollment should be directed by the State Women and Child Development Commission to implement intensive, scheme-specific DFL camps at Anganwadi centers on a quarterly basis, with content explicitly calibrated to DBT account management, Aadhaar-seeding, and navigation of the UMANG and Digi Locker platforms in conversational Marathi, not formal literary Marathi. Second, NABARD and the respective Lead District Managers must urgently augment banking correspondent density in sub-optimal districts to at least the RBI-prescribed norm of 1 BC per 1,000 rural population, with a mandated preference for the recruitment of women BCs directly addressing both the access deficit and the social constraint on rural women's engagement with male financial service providers documented in this study. Third, the weakest DFL sub-dimension Protective Digital Behaviour demands elevation to a standalone curriculum module in all financial education camps, delivered in partnership with the RBI's Centre for Financial Literacy networks, incorporating Marathi-language simulations of common UPI fraud scenarios tailored to the rural context. Fourth, a gender-responsive digital access policy that provides shared-access smartphones through existing Mahila Bichat Gat infrastructure could meaningfully address the 37.7% digital exclusion rate documented, converting existing SHG social trust networks into DFL dissemination channels. Fifth, government welfare delivery portals must mandatorily incorporate Marathi audio-guided navigation addressing Sangwan and Bahl's (2026) bureaucratic interface complexity barrier as a formal web accessibility standard for all schemes targeting Marathwada's rural women [20].

The cross-sectional design of this study precludes longitudinal tracking of DFL's impact on welfare outcomes over time; a two-to-three-year cohort study tracking the same beneficiaries would generate substantially more robust causal evidence while capturing the dynamic relationship between DFL acquisition and empowerment trajectories. The sample's restriction to registered beneficiaries potentially underrepresents the most marginalized women who have not entered the welfare scheme registration system a form of sampling bias that future research should address through community-based participatory sampling in non-registered populations. The study did not fully operationalize the mediating pathways between DFL and empowerment, which would be more rigorously examined through Structural Equation Modelling (SEM) with an expanded sample of $N \geq 500$. Future investigations should disaggregate the impact of specific welfare schemes (comparing PMMVY vs. PMJDY DFL-utilization relationships) and explicitly test Ndung'u's (2025) structural enablement layer through a three-condition moderated mediation model [4]. Cross-regional comparative studies contrasting Marathwada with Vidarbha, Konkan, or analogous distressed regions in Telangana, Andhra Pradesh, or Karnataka would enrich the comparative evidence base and validate the 'structural discount' mechanism proposed in the present study's discussion. Ultimately, while this study has established the primacy of DFL as a predictor of empowerment outcomes in rural Marathwada, the path toward genuine, equitable welfare scheme efficacy runs through the intersection of individual digital capability and institutional commitment to the enabling conditions that make that capability actionable.

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