



Impact of Digital Lending Platforms on SME Financing: A FinTech-Enabled Access-to-Finance Perspective on MSME Business Growth and Profitability

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ABSTRACT :

Micro, Small and Medium Enterprises (MSMEs) play a vital role in the economic development of emerging economies such as India. However, they continue to face significant financing challenges due to limited collateral, informal financial records, and insufficient credit histories. Financial Technology (FinTech) and digital lending platforms offer potential solutions by improving credit assessment, accelerating loan disbursement, and reducing transaction costs. This study examines the relationship between FinTech adoption, digital lending, and MSME performance, focusing on business growth and profitability, with access to finance serving as a mediating factor. The study proposes an integrated framework to understand how digital financial solutions influence MSME development and financial sustainability.

Data are collected through a structured Likert-scale questionnaire administered to employees and managers of MSMEs. The collected data are analysed using Microsoft Excel and statistical techniques, including chi-square tests, analysis of variance, multiple regression, and mediation analysis. The illustrative analysis based on simulated data indicates that FinTech adoption and digital lending positively influence MSME performance and improve access to finance. The findings also suggest that access to finance partially mediates the relationship between digital financial solutions and MSME performance. The study highlights the importance of digital financial services in addressing financing barriers and supporting business development. The proposed framework can help policymakers, financial institutions, and FinTech providers develop effective strategies to improve credit accessibility, enhance profitability, and promote the long-term sustainability of MSMEs.

Keywords: FinTech Adoption; Digital Lending; Access to Finance; MSME Performance; Business Growth; Profitability; Mediation Analysis

Introduction

Micro, Small and Medium Enterprises (MSMEs) play a key role in the Indian economy. They are commonly cited as accounting for a large share of manufacturing value added, non-agricultural employment and merchandise exports, and they are a backbone of inclusive growth because they create jobs with relatively low capital investment. However, MSMEs are also among the most financially constrained segments of the economy. Collateral, audited financial statements and a long credit history are key factors in assessing borrower risk, and many small businesses, especially those in informal sectors and in semi-urban and rural settings, lack them. The MSME financing gap is the difference between the credit that MSMEs need and the credit that formal institutions are willing to provide.

Over the last decade, the spread of smartphones and connectivity, the government's Digital India initiative, the Unified Payments Interface (UPI) and Aadhaar-enabled e-KYC have created a favourable environment for Financial Technology (FinTech). FinTech companies and digital lending platforms use alternative data such as transaction histories, GST records, utility payments and digital footprints to build credit profiles of borrowers who lack conventional documentation. These platforms have shortened origination, underwriting and disbursement from weeks to days, and sometimes hours, and have lowered the cost of reaching small, geographically dispersed borrowers. This trend has gained momentum since the COVID-19 pandemic, which increased the use of digital channels by both lenders and small business owners.

Against this background, an essential question is whether access to FinTech credit improves business outcomes for MSMEs. A sizeable literature documents FinTech as an industry phenomenon, but comparatively few studies examine the full chain from technology adoption, to improved access to finance, to firm-level growth and profitability. This paper addresses that gap by developing a framework, and a reproducible procedure for testing it, in which access to finance is the mechanism through which FinTech adoption and digital lending shape MSME performance. Because the proposed

questionnaire survey is yet to be administered, the empirical results reported in Section 5 are based on simulated data and illustrate the analytical procedure rather than provide empirical evidence.

The study makes three contributions. First, it distinguishes general FinTech usage from credit-specific digital lending and models both within a single framework. Second, it treats access to finance as a mediating mechanism rather than an end goal. Third, it offers a clear, reproducible Excel-based analytical procedure that practitioners and researchers without access to specialised software can use. The remainder of the paper is organised as follows. Section 2 reviews the literature, Section 3 presents the conceptual framework and hypotheses, Section 4 describes the methodology, and Section 5 reports the analysis. Section 6 discusses the results, Section 7 sets out the implications, Section 8 outlines limitations and future research, and Section 9 concludes.

Literature Review

Theoretical background

In this study, two main theoretical approaches will be followed. First, there is an aspect of technology acceptance. In his 1989 research, Davis found that acceptance of a technology will be more likely if people deem it useful and easy to use. The principles have since been used to the implementation of a wide range of financial technologies. The second viewpoint is the problem of information asymmetry and funding of SMEs. Berger and Udell described various lending practices in their 2006 paper, such as relationship, asset-based, and transaction-based lending, including credit-scoring, that may be used by lenders to make decisions when lending to small businesses with limited financial information. Likewise, Beck and Demirgüç-Kunt pointed out in 2006 that the availability of credit can constrain business expansion, especially for smaller companies. The present study builds on these perspectives, conceptualizing digital lending as a transaction-based financing model based on alternative data to judge a borrower, which also can help to decrease the reliance on traditional collateral and banking relationships. This will serve as the theoretical basis in exploring the impact of the application of FinTech and Digital Lending on MSME performance.

FinTech adoption among MSMEs

The TAM extensions have been frequently used in the study of technology acceptance in the financial sector. Hu et al. (2019) further developed the TAM model for the adoption intention of the FinTech among the bank users and concluded that perceived usefulness and ease of use have remained as strong predictors of adoption. Gupta, Agarwal and Nautiyal (2022) conducted survey research among registered MSMEs to identify that most MSMEs belong to the moderate FinTech adopter group and age, education and previous exposure to digital products of the MSME owner and manager influence the speed of FinTech adoption. However, more recently, Verma and Shome (2025) concluded that the extent of financial services that micro enterprises can access was positively linked to adoption intensity, which aligns with the notion that financial services are a stepping stone for more extensive financial inclusion and is consistent with the findings of other studies.

Digital lending platforms and credit accessibility

One of the prominent FinTech applications for MSMEs is digital lending. Research in alternative data-driven credit scoring, such as microlending through the use of the smartphone (Óskarsdóttir et al., 2020), demonstrates that alternative data can be used to predict repayment and, in some cases, to approximate and even under-perform traditional bureau scoring systems, allowing lenders to target previously unscored borrowers. It is not a utility-driven adoption where peer influence and word of mouth has been found to be significant influencing factors by Patil and Mehta (2021) in Indian SMEs' adoption of online lending platforms. A cross-country analysis at the policy level (World Bank, 2024) concludes that, together, digital loans, supply-chain finance platforms and e-invoicing can remove structural obstacles that have prevented SMEs from accessing formal credit, while digital literacy and regulatory clarity remain a barrier to adoption in emerging economies.

Access to finance as a mediating mechanism

In a smaller but rising segment, access to finance is a mediating variable that is not the end goal. Government support moderated the relationship between firm characteristics and the access to finance, and financial delinquency and the use of FinTech had a significant positive effect on access to finance for Indonesian MSMEs (PLS-SEM study, to be added). Tandilino et al. (2025) developed a model of digital financial inclusion as a mediator between the digital financial literacy, government support and MSME performance, and found that the mediated path accounted for a greater proportion of variance in MSME performance than the direct path. The results presented here reinforce the argument that access to finance is the channel through which the adoption of digital tools works to impact downstream outcomes.

MSME performance: business growth and profitability

There is little evidence available that shows the performance impacts of digital financial inclusion, and it is largely positive. Rahman (2023) found that there was an improvement in the availability of finance, as well as business performance, of the enterprises that adopted FinTech in Banten province. Further, Perez and Chen (2022) reported regional differences in FinTech adoption in Indonesia and suggested that performance effects were limited to the regions in which the digital infrastructure was more developed, suggesting that the FinTech–performance relationship might be tempered with the

context. The effects of digital credit's longer tenure, compared with short-term facilities, and eases repayment pressure, stabilising cash flow, were confirmed by a modelling exercise on digital-finance networks (PMC, 2024 [full citation to be added]).

Research gap

The literature reviewed above points to five gaps that this study addresses:

- Most of the literature is of a descriptive or policy nature, reflecting the growth of FinTech, but not measuring the impact of FinTech on the performance of the firm.
- Empirical studies tend to focus on adoption or intention to use and do not focus on downstream growth and profitability..
- Access to finance often seen as a final step, thus the indirect link between FinTech adoption and digital lending to performance is not widely tested.
- Despite the unique digital public infrastructure in India, most evidence of mediation is from outside Indian contexts (in Indonesia, Sub-Saharan Africa, and the United States).
- There are limited studies that model the adoption of FinTech and digital lending as separate but related predictor in the same model.

Conceptual Framework and Hypotheses

The model (Fig. 1) treats FinTech adoption (FA) and digital lending (DL) as independent variables, business growth (BG) and profitability (PR) as dependent variables, and access to finance (ATF) as the mediating variable that links the two sets. MSME performance (PERF) is the composite of BG and PR. The direct paths (H1, H2) run from FA and DL to PERF, and the indirect paths (H3–H5) run through ATF.

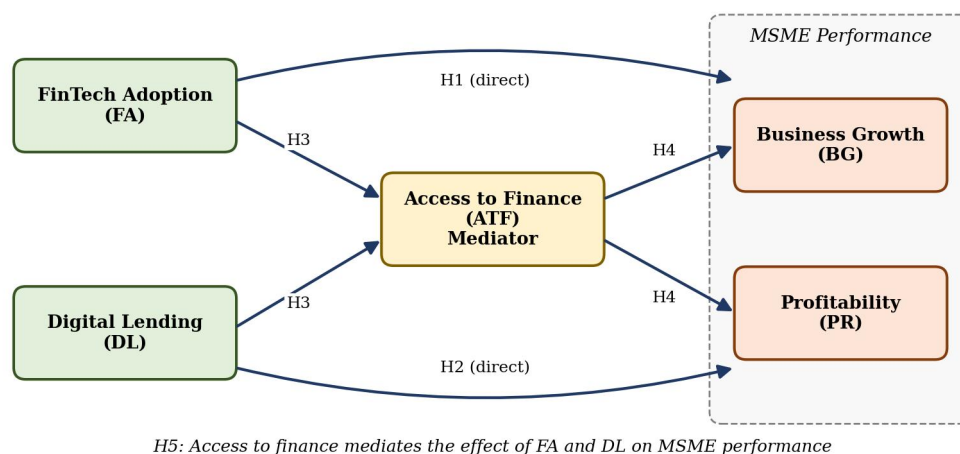


Fig. 1 - Conceptual framework.

Based on the research objectives, the following hypotheses are tested:

- **H1:** FinTech adoption has a positive and significant effect on MSME performance (business growth and profitability).
- **H2:** Digital lending has a positive and significant effect on MSME performance.
- **H3:** FinTech adoption and digital lending have a positive and significant effect on access to finance.
- **H4:** Access to finance has a positive and significant effect on MSME performance.
- **H5:** Access to finance mediates the relationship between FinTech adoption/digital lending and MSME performance (tested separately for FA, H5a, and DL, H5b).

Exploratory analyses of group differences are also conducted. Chi-square tests examine whether use of digital lending/FinTech platforms is associated with sector, enterprise size and years in operation, and one-way ANOVA examines whether MSME performance, access to finance and profitability differ by enterprise size, sector and years in operation, respectively.

Research Methodology

Research design

The study adopts a quantitative, cross-sectional, survey-based explanatory design. It tests hypothesised relationships between constructs using primary data collected from MSME respondents at a single point in time.

Population, sample and respondents

The target population comprises MSMEs in manufacturing, trading and services. Respondents are employees and managers working in the finance, operations, innovation and sustainability functions, together with owner-managers, as they are best placed to assess both technology use and financial and business outcomes. A sample of 250 respondents is targeted using stratified purposive sampling to ensure representation across sectors and size classes (micro: up to 10 employees; small: 11–50; medium: 51–250). This exceeds the common rule of thumb of ten respondents per questionnaire item (18 items) and the minimum needed for a regression with three predictors. In this version of the paper, a simulated data set of 250 respondents that follows this sampling frame is used to demonstrate the analysis (see Section 8).

Research instrument

Data are collected with a structured questionnaire (Section A: respondent and enterprise profile; Sections B–F: construct scales). All construct items are rated on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). Table 1 summarises the constructs.

Table 1 - Constructs and measurement

Construct	Code	Items	Example item
FinTech Adoption	FA	4 (FA1–FA4)	My enterprise regularly uses digital financial platforms (mobile banking, wallets, UPI) for business transactions.
Digital Lending	DL	4 (DL1–DL4)	Digital lending platforms have enabled faster disbursement of loans compared to traditional banks.
Access to Finance	ATF	4 (ATF1–ATF4)	It has become easier for my enterprise to access credit since adopting FinTech/digital lending.
Business Growth	BG	3 (BG1–BG3)	My enterprise has experienced an increase in sales after adopting FinTech/digital lending.
Profitability	PR	3 (PR1–PR3)	My enterprise's net profit margin has increased.

Note: Composite scores are the mean of each construct's items. MSME performance (PERF) is the mean of BG and PR.

Data analysis techniques

All analyses are performed in Microsoft Excel using formulas (no macros), so that every result updates when the data change. Results were cross-checked against an independent computation in Python and matched to at least six decimal places. The significance level is $\alpha = 0.05$.

- **Reliability and descriptives.** Cronbach's alpha (acceptable ≥ 0.70 ; Nunnally, 1978; Cronbach, 1951), means, standard deviations and Pearson correlations.
- **Chi-square test of independence** for associations between categorical variables (Eq. 1). Effect size is Cramér's V. Excel functions: COUNTIFS, CHITEST, CHIINV.
- **One-way ANOVA** for differences in mean scores across three or more groups (Eq. 2), with effect size $\eta^2 = SS_{\text{between}} / SS_{\text{total}}$, followed by Bonferroni-adjusted pairwise t-tests. Excel functions: AVERAGEIF, SUMPRODUCT, FDIST, FINV, TDIST.
- **Multiple linear regression** (OLS) estimated with LINEST and reported with unstandardised coefficients, standard errors, t, p, standardised β , R^2 , adjusted R^2 and F. Multicollinearity is checked with the variance inflation factor (VIF). The four models are given in Eqs. (4)–(7).
- **Mediation analysis** following Baron and Kenny (1986): (1) $X \rightarrow Y$ (total effect c); (2) $X \rightarrow M$ (path a); (3) $M \rightarrow Y$ controlling for X (path b) and the direct effect c'. The indirect effect $a \times b$ is tested with the Sobel (1982) test (Eq. 3).

$$\chi^2 = \sum \frac{(O-E)^2}{E}, df = (r-1)(c-1) \quad (1)$$

$$F = \frac{MS_{\text{between}}}{MS_{\text{within}}} \quad (2)$$

$$Z = \frac{ab}{\sqrt{b^2 SE_a^2 + a^2 SE_b^2}} \quad (3)$$

$$PERF = \beta_0 + \beta_1 FA + \beta_2 DL + \varepsilon \quad (4)$$

$$ATF = \beta_0 + a_1 FA + a_2 DL + \varepsilon \quad (5)$$

$$PERF = \beta_0 + b ATF + \varepsilon \quad (6)$$

$$PERF = \beta_0 + c'_1 FA + c'_2 DL + b ATF + \varepsilon \quad (7)$$

In Eqs. (4)–(7), Model 1 regresses PERF on FA and DL; Model 2 regresses ATF on FA and DL; Model 3 regresses PERF on ATF; and Model 4 regresses PERF on FA, DL and ATF.

Ethical considerations

Participation is voluntary and anonymous; the enterprise name is optional, respondents give informed consent, and responses are reported only in aggregate.

Data Analysis and Results***Respondent and enterprise profile***

Table 2 describes the 250 respondents. The sample is spread across manufacturing, trading and services, and across micro, small and medium enterprises. In total, 180 enterprises (72.0%) reported having used a digital lending or FinTech platform.

Table 2 - Respondent and enterprise profile (n = 250)

Variable / category	Frequency	Percent
Sector		
Manufacturing	97	38.8%
Trading	86	34.4%
Services	67	26.8%
Years in operation		
Less than 3 years	41	16.4%
3–5 years	59	23.6%
6–10 years	71	28.4%
More than 10 years	79	31.6%
Enterprise size		
Micro (up to 10)	78	31.2%
Small (11–50)	109	43.6%
Medium (51–250)	63	25.2%
Functional area		
Finance	77	30.8%
Operations	76	30.4%
Innovation	47	18.8%
Sustainability	19	7.6%
Other	31	12.4%
Respondent role		
Owner	74	29.6%
Manager	115	46.0%
Senior Employee	52	20.8%
Other	9	3.6%
Used digital lending/FinTech		
Yes	180	72.0%
No	70	28.0%

Source: Excel workbook, sheet 'Demographics' (simulated data).

Reliability and descriptive statistics

Cronbach's alpha ranged from 0.77 to 0.83 across the five constructs, indicating acceptable to good internal consistency (Table 3). Mean scores cluster around 3.3 on the five-point scale, indicating moderate agreement overall.

Table 3 - Descriptive statistics and reliability

Construct	Items	Mean	SD	Min–Max	Cronbach's α	Reliability
FinTech Adoption (FA)	4	3.29	0.84	1.3–5.0	0.815	Good
Digital Lending (DL)	4	3.31	0.85	1.0–5.0	0.830	Good
Access to Finance (ATF)	4	3.30	0.82	1.5–5.0	0.834	Good

Construct	Items	Mean	SD	Min–Max	Cronbach's α	Reliability
Business Growth (BG)	3	3.27	0.85	1.0–5.0	0.767	Acceptable
Profitability (PR)	3	3.27	0.86	1.7–5.0	0.770	Acceptable
MSME Performance (PERF)	6	3.27	0.70	1.5–5.0	0.768	Acceptable

Note: PERF reliability is computed over all six BG and PR items.

Correlation analysis

Table 4 shows positive, moderate correlations among all constructs ($|r| > 0.124$ is significant at $\alpha = 0.05$ for this sample size). Among the predictors, access to finance has the strongest association with MSME performance ($r = 0.61$). VIF values for FA, DL and ATF are all below 1.5, so multicollinearity is not a concern.

Table 4 - Pearson correlation matrix

	FA	DL	ATF	BG	PR	PERF
FA	1.00	0.46	0.38	0.38	0.39	0.46
DL	0.46	1.00	0.46	0.42	0.41	0.51
ATF	0.38	0.46	1.00	0.53	0.48	0.61
BG	0.38	0.42	0.53	1.00	0.35	0.82
PR	0.39	0.41	0.48	0.35	1.00	0.82
PERF	0.46	0.51	0.61	0.82	0.82	1.00

Note: All off-diagonal correlations are significant at $p < .05$.

Chi-square tests of independence

Three chi-square tests examined whether use of digital lending platforms is associated with enterprise characteristics (Table 5). All expected cell counts exceeded 5 (minimum = 11.48), so the test assumptions are met. Platform use differed significantly by enterprise size, $\chi^2(2) = 15.84$, $p < .001$, Cramér's $V = 0.252$: 85.7% of medium enterprises had used a platform compared with 56.4% of micro enterprises. The association with sector was weaker but significant, $\chi^2(2) = 6.15$, $p = .046$, $V = 0.157$, with the highest use in services. No association was found with years in operation, $\chi^2(3) = 0.32$, $p = .957$.

Table 5 - Chi-square tests – use of digital lending/FinTech platform

Cross-tabulation	χ^2	df	p-value	Cramér's V	Decision ($\alpha = .05$)
Sector $\times$ Platform use	6.147	2	.046	0.157	Significant association
Enterprise size $\times$ Platform use	15.845	2	< .001	0.252	Significant association
Years in operation $\times$ Platform use	0.315	3	.957	0.036	No significant association

Source: Excel workbook, sheet 'ChiSquare' (observed and expected tables for all three tests).

Table 6 - Observed counts – enterprise size $\times$ platform use

Enterprise size	Used platform	Did not use	Total
Micro (up to 10)	44	34	78
Small (11–50)	82	27	109
Medium (51–250)	54	9	63
Total	180	70	250

Source: Excel workbook, sheet 'ChiSquare'.

One-way ANOVA

Table 7 reports three ANOVAs. MSME performance differed significantly by enterprise size, $F(2, 247) = 4.78$, $p = .009$, $\eta^2 = 0.037$; mean performance rose from 3.11 (micro) to 3.28 (small) and 3.47 (medium). Bonferroni comparisons show that only micro and medium enterprises differ significantly ($p = .007$). Access to finance differed by sector, $F(2, 247) = 3.86$, $p = .022$, $\eta^2 = 0.030$, with services reporting the highest scores; the manufacturing–services difference was the only significant pair ($p = .018$). Profitability did not differ by years in operation, $F(3, 246) = 0.25$, $p = .865$. Effect sizes for the significant results are small ($\eta^2 \approx .03$ –.04).

Table 7 - One-way ANOVA results and group means

Analysis / group	Statistic	Spread / p	Effect size
PERF by enterprise size	F(2, 247) = 4.78	p = .009	$\eta^2 = 0.037$
Micro (up to 10) (n = 78)	M = 3.11	SD = 0.62	
Small (11–50) (n = 109)	M = 3.28	SD = 0.71	
Medium (51–250) (n = 63)	M = 3.47	SD = 0.73	
ATF by sector	F(2, 247) = 3.86	p = .022	$\eta^2 = 0.030$
Manufacturing (n = 97)	M = 3.15	SD = 0.87	
Trading (n = 86)	M = 3.30	SD = 0.79	
Services (n = 67)	M = 3.51	SD = 0.75	
PR by years in operation	F(3, 246) = 0.25	p = .865	$\eta^2 = 0.003$
Less than 3 years (n = 41)	M = 3.35	SD = 0.96	
3–5 years (n = 59)	M = 3.32	SD = 0.82	
6–10 years (n = 71)	M = 3.24	SD = 0.75	
More than 10 years (n = 79)	M = 3.23	SD = 0.92	

Source: Excel workbook, sheet 'ANOVA' (includes the full ANOVA tables and Bonferroni pairwise comparisons).

Multiple regression analysis

Table 8 presents the regression models. In Model 1, FinTech adoption and digital lending jointly explain 32.3% of the variance in MSME performance, $F(2, 247) = 58.99$, $p < .001$; both coefficients are positive and significant, supporting H1 and H2. Digital lending has the larger effect ($\beta = 0.37$ versus 0.29 for FA). In Model 2, FA and DL explain 24.7% of the variance in access to finance and both are significant, supporting H3. Model 3 shows that access to finance strongly predicts MSME performance ($B = 0.521$, $p < .001$, $R^2 = 0.372$), supporting H4. When all three predictors enter together (Model 4), R^2 rises to 0.466 (an increase of 0.143 over Model 1) and access to finance is the strongest predictor ($\beta = 0.44$), while FA and DL remain significant.

Table 8 - Regression results – unstandardised B (standard error)

Predictor	M1: PERF	M2: ATF	M3: PERF	M4: PERF
Constant	1.452*** (0.172)	1.452*** (0.212)	1.554*** (0.146)	0.911*** (0.167)
FA	0.245*** (0.049)	0.208*** (0.061)	–	0.168*** (0.045)
DL	0.306*** (0.049)	0.350*** (0.060)	–	0.175*** (0.046)
ATF	–	–	0.521*** (0.043)	0.372*** (0.046)
R²	0.323	0.247	0.372	0.466
Adjusted R ²	0.318	0.241	0.369	0.460
F	58.99	40.62	146.88	71.65
p (F)	< .001	< .001	< .001	< .001

Note: n = 250. * $p < .05$, ** $p < .01$, *** $p < .001$. Source: Excel workbook, sheet 'Regression'.

Table 9 repeats the full model separately for each performance dimension. Access to finance is the strongest predictor of both business growth and profitability, and both FA and DL retain significant positive effects.

Table 9 - Predictors of business growth and profitability

Predictor	BG: B	β	p	PR: B	β	p
FA	0.151*	0.15	.014	0.185**	0.18	.004
DL	0.167**	0.17	.008	0.183**	0.18	.005
ATF	0.409***	0.40	< .001	0.336***	0.32	< .001
R²	0.335			0.299		

Note: BG = business growth; PR = profitability. * $p < .05$, ** $p < .01$, *** $p < .001$.

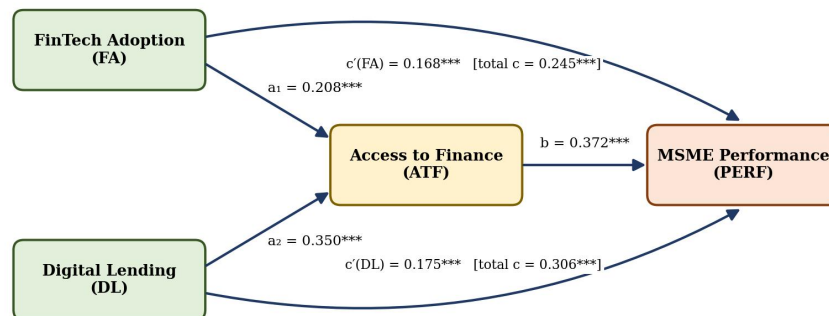
Mediation analysis

Table 10 and Fig. 2 summarise the mediation tests. The total effects of FA ($c = 0.245$) and DL ($c = 0.306$) on performance were significant (Step 1); both predicted access to finance (Step 2); and access to finance predicted performance when FA and DL were controlled ($b = 0.372$, Step 3). The indirect effects were significant in the Sobel test: for FA, $ab = 0.077$, $z = 3.15$, $p = .002$, 95% CI $[0.029, 0.126]$; for DL, $ab = 0.131$, $z = 4.73$, $p < .001$, 95% CI $[0.076, 0.185]$. Because the direct effects c' remained significant, access to finance **partially** mediates both relationships, accounting for about 31.6% (FA) and 42.7% (DL) of the total effects. H5 is therefore supported.

Table 10 - Mediation results (Baron–Kenny steps and Sobel test)

Quantity	FA → ATF → PERF	DL → ATF → PERF
Total effect c	0.245	0.306
p-value of c	< .001	< .001
Path a ($X \rightarrow ATF$)	0.208	0.350
p-value of a	< .001	< .001
Path b ($ATF \rightarrow PERF \mid X$)	0.372	0.372
p-value of b	< .001	< .001
Direct effect c'	0.168	0.175
p-value of c'	< .001	< .001
Indirect effect $a \times b$	0.077	0.131
Sobel z	3.15	4.73
Sobel p-value	.002	< .001
95% CI of $a \times b$	$[0.029, 0.126]$	$[0.076, 0.185]$
Proportion mediated	31.6%	42.7%
Conclusion	Partial mediation	Partial mediation

Source: Excel workbook, sheet 'Mediation'. CI = $a \times b \pm 1.96 \times \text{Sobel SE}$.



Unstandardised coefficients. * $p < .05$, ** $p < .01$, *** $p < .001$, ns = not significant. Simulated placeholder data.

Fig. 2 - Path model with estimated coefficients (simulated placeholder data).

Summary of hypothesis tests

Table 11 summarises the outcome of each hypothesis test on the simulated data set.

Table 11 - Hypothesis test summary

No.	Relationship	Test statistic	Decision
H1	FA → PERF (+)	$B = 0.245$, $p < .001$	Supported
H2	DL → PERF (+)	$B = 0.306$, $p < .001$	Supported
H3	FA, DL → ATF (+)	$R^2 = 0.247$, both $p < .001$	Supported
H4	ATF → PERF (+)	$B = 0.521$, $p < .001$	Supported
H5a	ATF mediates FA → PERF	$ab = 0.077$, $z = 3.15$, $p = .002$	Supported (partial)
H5b	ATF mediates DL → PERF	$ab = 0.131$, $z = 4.73$, $p < .001$	Supported (partial)

Discussion

The illustrative results are in line with the theory, which suggests that FinTech and digital lending have a primary impact on MSMEs outcomes by easing financing constraints. Three trends are evident. First, the association of digital lending to performance was greater than general FinTech adoption (total effects of 0.31 and 0.25), consistent with an argument that credit-specific platforms are more closely aligned with the financing mechanism than are payment and bookkeeping applications. Second, the significant indirect effects (32% to 43% of the total effect) indicate that access to finance is one, but not the only, channel; the rest of the direct effects could be related to efficiency gains, better data and market access not mediated by borrowing. Third, larger enterprises (by volume) were more likely to use the platform and perform well on it, offering further support for the previously mentioned digital illiteracy and infrastructure concerns (Perez & Chen, 2022; World Bank, 2024).

The results of the group differences were small. The chi-square effects are small to moderate (Cramér's $V = .16$ for sector and $.25$ for size) and the ANOVA effects are small ($\eta^2 \approx .03-.04$), meaning that size and sector should be interpreted as contextual factors, rather than overwhelming influences. When comparing the findings by the years in operation, there was no significant difference between the groups, indicating that the influence of firm age is not the only factor to consider when deciding on the adoption or impact of digital lending. These interpretations are based on the simulated data and may be updated after analysing real responses.

Implications

For policymakers. Once proven with actual data, policies that will deepen digital public infrastructure (UPI, e-KYC, GST data-sharing), and improve digital financial literacy, can improve MSME performance by increasing credit access. Specific support for micro enterprises would be the most direct solution to the gap, as these platforms are used the least.

For financial institutions and Fin Techs. The features that respondents are invited to assess are: faster disbursal, easy filing and alternative credit scoring; having a confirmation of their linkage to access to finance would assist lenders to prioritize product design. Bank-FinTech collaborations can help with reach to smaller companies.

For owners and managers of MSMEs. The questionnaire constructs can be used as a self-assessment of digital financial readiness, and combining routine use of digital financial tools with credit-specific digital platforms may provide greater benefits than using either alone.

Limitations and Future Research

- The results in this paper are based on simulated data; no substantive conclusions can be drawn until real data replace them.
- The design is cross-sectional, which limits causal inference and leaves the study open to common method bias. Perceptual items on growth and profitability could be supplemented with financial statement data.
- The Baron–Kenny/Sobel approach assumes that the indirect effect is normally distributed, which is generally not the case; bootstrapped confidence intervals are recommended. The Excel-based regression approach also cannot model measurement error in latent constructs.
- Future research should confirm the model using partial least squares SEM (PLS-SEM) or covariance-based SEM, test digital literacy, government support or regional infrastructure as moderators, and use longitudinal data.

Conclusion

This paper proposed and illustrated a mediation model in which FinTech adoption and digital lending improve the growth and profitability of MSMEs by easing access to finance. Using a questionnaire of five constructs and 18 items and an Excel-based mediation analysis of five hypotheses, the illustrative analysis supports all five hypotheses and shows partial mediation by access to finance. Once the workbook is populated with actual survey responses, the same procedure will provide empirical evidence for India to guide policymakers, lenders, FinTech providers and MSME managers.

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Declarations

Ethics and consent. Participation was voluntary and consent was implied by completing the anonymous online questionnaire. No institutional ethics approval or exemption is documented for this study.

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Author contributions. Myla Mahalakshmi: conceptualization, methodology, formal analysis, data curation, writing – original draft.

Dr. I. Mohan Krishna: supervision, validation, writing – review and editing. Both authors have read and approved the final manuscript.

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