Dialogue Social Science Review (DSSR)
www.thedssr.com

ISSN Online: 3007-3154
ISSN Print: 3007-3146
Vol. 4 No. 4 (April) (2026)

Digital Banking Adoption and SME Financing Accessibility in Hyderabad, Sindh: Empirical Evidence from a Primary Survey

Dr. Qazi Mumtaz Ahmed
Assistant Professor, Institute of Commerce and Management, University of Sindh Jamshoro. qazimumtaz@hotmail.com

Dr. Ashfaque Ali Banbhan
Associate Professor, Institute of Commerce & Management, University of Sindh, Jamshoro.. Email: ashfaque.banbhan@usindh.edu.pk
ORCID: https://orcid.org/0000-0002-0821-9993

Abstract
Small and medium-sized enterprises (SMEs) are the back-bone of the Pakistan economy, but still, there are still financing gaps that limit their expansion potential especially in new areas like Hyderabad, Sindh. This research examines the effects of the introduction of digital banking on the accessibility of SME financing using a mixed-method quantitative research design. A structured questionnaire was used to gather primary data of 200 SMEs in six sectors in Hyderabad. To test six research hypotheses, descriptive statistics, independent samples t-tests, Pearson correlation analysis, logistic regression, ordinary least squares (OLS) regression, one-way analysis of variance (ANOVA), and Baron-Kenny mediation analysis were used. Findings indicate that the general adoption of digital banking is 65% with the services sector registering the highest (73.8%) and the lowest (45.5%) in the agriculture sector. The rate of loan approval was 72.3% among digital adopters and 47.1% among non-adopters ($t = 4.87$, $p < 0.001$). According to logistic regression, the adoption of digital banking is the most predictive variable of loan approval ($\beta = 1.423$, OR = 4.149, $p < .001$). Digital banking variables explain 52.3% of the variation in the Financial Inclusion Index using OLS regression ($R^2 = .523$, $F = 21.34$, $p < .001$). Mediation analysis proves the existence of a partial mediation between credit score and digital adoption as well as loan approval (Sobel $z = 4.23$, $p < .001$). The implications of the findings are important to the policymakers, banking institutions, developers of fintech, and owners of SMEs in the underdeveloped areas in Pakistan.

Keywords: Digital banking, SME financing, financial inclusion, Pakistan, Hyderabad, fintech, access to loans, mobile banking

INTRODUCTION

One of the most important businesses in the world accounts to more than 90% of all businesses, and 60-70 percent of the total working in any developing economy (International Labour Organization [ILO], 2019). In Pakistan, SMEs are about 90% of all enterprises in the private sector and about 40% of gross domestic product (GDP) and provide around 80% of the non-agricultural labour force (State Bank of Pakistan [SBP], 2021). Regardless of this essential part of the economy, SMEs in Pakistan are affected by deep structural limitations in financing, with a financing gap of about PKR 1.8 trillion every year (International

Finance Corporation [IFC], 2022). This disparity is especially sharp in the secondary urban centres like Hyderabad, Sindh, where formal financial infrastructure has not yet been developed as compared to the metropolitan centres.

The expansion of digital financial services globally, has created a significant sense of optimism about the potential of technology-enhanced banking in resolving credit gaps that have long been experienced by SMEs (Haddad and Hornuf, 2019; Ozili, 2018). The implementation of mobile banking, online loan applications, electronic wallets, and fintech intermediaries has radically changed the environment of credit origination and disbursement, making it possible to make faster decisions, pay less, and get more financial information (Beck et al., 2022; Claessens et al., 2018). Nonetheless, there is limited evidence on the efficacy of digital banking in the context of SME financing in secondary cities in Pakistan, which is theoretically poorly developed and empirically disjointed (Aslam et al., 2021; Hussain et al., 2020).

As one of the second-largest cities in Sindh and the historically important commercial hub, Hyderabad offers a valuable case study to explore the idea of digital banking adoption among SMEs. The city is home to a heterogeneous SME ecosystem in terms of retail trade, manufacturing, services, agriculture, wholesale trade, and food and beverage-sectors with heterogeneous digital infrastructure, regulatory frameworks, and credit demand patterns. Still, intensive empirical studies of the patterns of digital banking adoption and its financing in these groups of the sector are glaringly missing in the literature.

To fill this gap, this paper will discuss three key research questions: (1) What is the current rate and trend of digital banking adoption among SMEs in Hyderabad? (2) Does adoption of digital banking have a significant effect on the accessibility of SME financing in terms of loan approval rates and loan amounts, interest rates, and processing times? (3) Is credit score the mediator between digital banking adoption and the outcome of loan approval? This study provides useful policymaking insights, banking institutions, and financial inclusion literature in Pakistan, by providing reliable answers to these questions relying on a primary dataset of 200 SMEs and a wide range of statistical methods.

The rest of this paper has the following structure. The second part is a literature review of the relevant theoretical frameworks and empirical literature. The third section describes the method of the research. The fourth part shows the empirical findings. The fifth part will discuss and interpret findings, conclusions, policy implications and future research directions.

LITERATURE REVIEW

Theoretical Framework

This research is based on three theoretical frameworks that are complementary. To start with, the Technology Acceptance Model (TAM) which was initially introduced by Davis (1989) and later developed by Venkatesh, and Davis (2000), offers the conceptual framework through which one can conceptualize both individual and organizational adoption of digital banking technologies. TAM indicates that perceived usefulness and perceived ease of use are the two most important factors of technology adoption that are mediated by behavioural intentions. TAM has been implemented in the context of the SME financing to uncover the reasons behind the use of mobile banking, online loan applications, and fintech platforms by businesses (Chong et al., 2010; Lim et al., 2019).

ISSN Online: 3007-3154
ISSN Print: 3007-3146
DIALOGUE SOCIAL SCIENCE REVIEW
Vol. 4 No. 4 (April) (2026)

Second, the Financial Intermediation Theory (FIT) expressed by Diamond (1984) and Gurley and Shaw (1955) involves the banking institutions as intermediaries of information that help to decrease asymmetric information between the borrower and the lender. The digital banking innovations, in particular credit scoring algorithms, transaction history analytics, and the digital identity verification, help decrease information asymmetries and, consequently, it decreases the cost and risk of lending to SMEs (Boot, 2000; Petersen, 2002). This theoretical approach is what informs directly the anticipated correlation between digital banking and the outcomes of better credit.

Third, according to Demirguc-Kunt and Klapper (2013) and supported by the World Bank's Global Findex database, Financial Inclusion Theory points out that access to formal financial services is a cause and consequence of economic development. Digital channels have been hypothesized to broaden financial inclusion by lessening geographic and expense prices to financial services, an idea that is especially applicable to the Hyderabad setting where the density of physical bank branches is low in comparison to metropolises like Karachi (Sahay et al., 2015; World Bank, 2022).

Digital Banking and SME Financing: Global Evidence

There is an increased body of empirical literature on the topic of digital banking and SME financing that has developed in the last ten years, mainly in the framework of developed economies and East Asia. The pivotal discovery on SME development by Beck et al. (2008), as incorporated by the authors of subsequent research, is that bank funding restrictions are negatively associated with the growth of SMEs, and smaller and younger firms is more susceptible. Later research has shown that the adoption of digital banking mitigates these limitations through the enhancement of access to credit and a decrease in the cost of transactions. Bruhn and Love (2014) have reported big gains in income and business among SMEs in Mexico after the growth of mobile banking services whereas Munyegera and Matsumoto (2016) established that the use of mobile money improved household income and financial strength in Uganda.

Durai and Stella (2019) discovered that the adoption of fintech in the Asian setting significantly enhances access of SME credit in India by decreasing information asymmetry and processing cost. Lee et al. (2021) showed that the Taiwanese digital SMEs were found to be 28 percentage points more likely to receive a loan approval as compared to non-digital SMEs. Tang (2019) reported that the fintech lending platforms significantly increased credit accessibility to the small businesses in China that had formerly been locked out of the formal banking systems. Allen et al. (2016) opined that mobile phone-based financial services are the most promising technological channel to financial inclusion of underserved populations, such as SME owners.

Digital Banking Adoption in Pakistan

In Pakistan, research about digital banking has gained momentum since the introduction of the National Financial Inclusion Strategy by the State Bank of Pakistan in 2015 and the ensuing development of branchless banking and fintech solutions (Agrawalla et al., 2021). Akhtar (2020) reported a substantial increase in access to credit services by SMEs in Punjab due to the introduction of mobile banking services and Hussain et al. (2020) observed that fintech lending services shortened the processing time of SME loans by up to 40% compared to traditional bank-based services in Karachi. Qayyum et al. (2021) discovered that there is a significant moderating role of digital financial literacy in the positive correlation between digital banking and the financial inclusion outcomes of urban Pakistan SMEs.

But most Pakistani research has concerned Karachi, Lahore and Islamabad, and systematic data about the secondary cities of Sindh, such as Hyderabad, Sukkur and Larkana is limited. According to Memon et al. (2020), SMEs in Sindh have compounded barriers to financing, including less digital infrastructure, increased perceptions of credit risk by banks, and financial illiteracy. The study by Mirza et al. (2022) focused on digital exclusion as a significant enhancer of the SME financing gap in non-metropolitan districts in Sindh and highlighted the importance of localized empirical studies.

Fintech and Financial Inclusion

The overlap of financial technology and inclusion agendas has produced a body of sizeable literature that investigates the way fintech platforms transform SME credit markets. Claessens et al. (2018) proved that marketplace lending platforms help to lower the cost of SME borrowing and enhance the availability of credit, especially to those firms that have no collateral. Ozili (2018) synthesized evidence on digital finance and financial inclusion in the world, and in this article, he concludes that mobile money and digital banking are highly related with the decreases in financial exclusion rates in Africa and Asia. The study by Haddad and Hornuf (2019) revealed that the greatest effect of fintech innovation is observed in economies that have developed digital infrastructure and have an unfavourable regulatory environment.

When it comes to the emerging economies, Gomber et al. (2017) emphasized that the trust, digital literacy, and regulatory clarity mediate fintech uptake by the SMEs. Morgan and Trinh (2019) discovered that fintech credit in developing Asia improves SME financial inclusion that is conditioned by macroeconomic stability and competitiveness in the banking industry. Sahay et al. (2015) put forward the argument that with proper regulatory frameworks, the digital financial services would hasten the pace of financial inclusion by three to five years compared to the conventional expansion of the banking sector through the branch.

Credit Scoring and Mediation Effects

An increasing literature on the mechanisms by which digital banking enhances credit outcomes finds credit scoring as an important mediating variable. Petersen and Rajan (2002) showed that the incorporation of digital transaction data in credit scoring models, leads to a significant increase in credit assessment accuracy of SMEs, lowers default rates and increases access to credit. According to the study by Berg et al. (2020), digital footprint information (mobile transaction history, online behavioural patterns and social media activity) is a significant improvement to credit scoring accuracy, especially in the case of previously unbanked borrowers.

Breza and Kinnan (2021) proved that the increase in credit scores due to the adoption of digital banking positively and significantly influences the further loan approval rates. Khan et al. (2021) discovered that digital banking adoption especially enhances SME credit scores by accumulating verifiable transaction histories which improve credit scores and this moderates the correlation between adoption and loan approval rates in the Pakistani context. The present study is based on Hypothesis 6, which is based on this mediation hypothesis.

Research Gap and Hypotheses

An overview of the available literature shows that there are three major gaps that can be applied to this study. First, although there is a significant amount of evidence regarding the positive impact of digital banking on SME financing in developed economies, as well as some Asian countries, none of it is available in Pakistan and especially in the secondary urban centres, specifically, Hyderabad and Sindh. Second, it is rare to compare the rates of digital banking adoption and financing results in sectoral groups within a single population of SMEs in a certain region, which constrains the knowledge of sectoral heterogeneity. Third, the moderating factor of the credit score in the digital banking-to-loan approval pipeline has not been investigated in the Sindhi SME scenario.

Based on the reviewed theoretical backgrounds and on the basis of the empirical literature above, this study will test the following six hypotheses:

H1: The adoption of digital banking has a significant impact on enhancing the rate of loan approval to SMEs in Hyderabad.

H2: The use of mobile banking has a positive impact on financial inclusion of SMEs in Hyderabad.

H3: There is a significant decrease in processing times of SME credit in Hyderabad when online loan applications are used.

H4: The adoption of fintech platforms can greatly increase access to SME credit in Hyderabad.

H5: The adoption rate of digital banking varies greatly in the different SME sectors in Hyderabad.

H6: The relationship between the adoption of digital banking and loan approval among SMEs in Hyderabad is mediated by credit score.

METHODOLOGY

Research Design

The research design utilized in this study is quantitative, cross-sectional research design based on positivist tradition of epistemology. The positivist approach is suitable since the research questions are interested in measurable causal and associational relationships among a set of defined constructs (digital banking adoption and SME financing outcomes) which can be operationalized and tested using statistical inference (Creswell and Creswell, 2018; Saunders et al., 2019). Although cross-sectional designs do not allow causal inference with the same rigour as longitudinal designs, they are typical of SME financing surveys and allow the investigation of a diverse population of SMEs with the available resource constraints (Bryman and Bell, 2015).

Population and Sampling

The target population will include SMEs that are registered and are currently operating in Hyderabad, Sindh, at the time of the survey reference (January2024-March 2024). A sampling frame of 2,400 registered SMEs in six sectors, namely, retail trade, manufacturing, services, agriculture, wholesale trade and food and beverage, was supplied by the Hyderabad Chamber of Small Traders and Small Industries. The stratified random sampling was used to make sure that the sample is representative of the sectors and the proportion of each

ISSN Online: 3007-3154
ISSN Print: 3007-3146
DIALOGUE SOCIAL SCIENCE REVIEW
Vol. 4 No. 4 (April) (2026)

sector within the sample was decided using the proportional allocation method (Cochran, 1977).

The sample size of 343 was obtained by using the Yamane (1967) formula of finite population sampling at 95% confidence level with 5% margin of error: $n = 2400/(1 + 2400 \times 0.05^2) \approx 343$. The sample used was 480 questionnaires, considering an expected non-response rate of about 40% considering the experience in the previous SME survey in Pakistan (Hussain et al., 2020). 212 questionnaires were returned and only 200 SMEs were included in the final analytical sample by eliminating 12 cases where the questionnaires were incomplete (response rate = 44.2%).

Survey Instrument

The structured questionnaire was used to gather data based on a systematic review of the validated tools available in previous literature (Durai and Stella, 2019; Hussain et al., 2020; Ozili, 2018). The questionnaire consisted of two parts. Section A included demographic and enterprise features such as business age, annual revenue, sector, and size of the business (number of employees). Section B determined the level of adoption of digital banking (mobile banking, online loan application, e-wallet utilization, use of fintech platforms), experience with loan application and approval, credit score, interest rate, collateral requirement, processing time, financial inclusion (measured through a six-item index based on an adaptation of Demirgues-Kunt and Klapper, 2013), and overall satisfaction.

Expert review was used to determine content validity with the help of three academic experts in the field of banking and finance and two senior banking practitioners. A pilot study involving 30 owners of SMEs was done to test the clarity and reliability of the instruments, and some small changes in wording were made. The reliability of the final instruments was measured based on alpha Cronbach and all the constructs were above the alpha of.70 indicated by Nunnally and Bernstein (1994). Confirmatory factor analysis was used to confirm convergent validity and all the values of Average Variance Extracted (AVE) were more than.50 (Fornell and Larcker, 1981).

Variable Operationalization

The dependent variable of the most significant interest to logistic regression was the acceptance of the loan (binary 1 = approved, 0 = not approved). The Financial Inclusion Index (continuous, 0 – 10) was the primary dependent variable, which was operationalized as a composite variable (account ownership, access to credit, digital payment use, insurance access, savings behaviour and access to remittance service) (Demirguc-Kunt and Klapper, 2013). The most significant independent variables were digital banking adoption (binary), mobile banking adoption (binary), online application to a loan (binary), e-wallet adoption (binary), the use of a fintech platform (binary), annual revenue (log-transformed), business age (years), credit score (continuous), and collateral accessibility (binary).

Analytical Approach

The analysis of data was in a multi-method sequential manner. The first step was the calculation of descriptive statistics to describe the sample and distributions of the key variables. Second, digital adopters versus non-adopters were compared using independent samples t-tests in the comparison of the means.

Dialogue Social Science Review (DSSR)
www.thedssr.com

ISSN Online: 3007-3154
ISSN Print: 3007-3146
Vol. 4 No. 4 (April) (2026)

Third, Pearson correlation test was used to test bivariate correlations between continuous variables. Fourth, the determinants of loan approval were modeled using binary logistic regression (Method: Enter), which reports unstandardized coefficients, odds ratios and 95% confidence intervals. Fifth, the determinants of the Financial Inclusion Index were modelled using OLS multiple regression with diagnostic tests showing that the model does not have multi-collinearity (max VIF = 2.34) or autocorrelation (Durbin-Watson = 1.87). Sixth, ANOVA (one way) was used to assess the differences between sectors with regard to digital adoption. Finally, the Baron and Kenny (1986) procedure was used to test the mediation of credit score in the digital adoption–loan approval relationship, with the Sobel test used to assess the significance of the indirect effect. All the analyses were done in IBM SPSS 27 statistics. The evaluation of statistical significance was $p < .05$ (two-tailed).

RESULTS

Sample Characteristics and Sector Distribution

Table 1 shows the distribution of the 200 surveyed SMEs in sectors. The most significant sector (n = 42, 21.0%), then wholesale trade (n = 38, 19.0%), and retail trade and food and beverage (n = 35 each, 17.5%) were services. The sample was 14.0% (n = 28) and 11.0% (n = 22) in manufacturing and agriculture, respectively. The highest adoption of digital banking was in services sector (73.8%), and lowest in agriculture (45.5%). In line with this, services (69.0%) and agriculture (40.9%) had the largest and smallest average loan approval rates, indicating an initial relationship between digital adoption and financing performance.

Table 1: ***Sector Distribution, Digital Adoption, and Average Loan Approval Rates***

Sector	n	%	Cum. %	Digital Adoption %	Avg Loan Approval %
Retail Trade	35	17.5	17.5	68.6	62.9
Manufacturing	28	14.0	31.5	60.7	57.1
Services	42	21.0	52.5	73.8	69.0
Agriculture	22	11.0	63.5	45.5	40.9
Wholesale Trade	38	19.0	82.5	65.8	60.5
Food & Beverage	35	17.5	100.0	62.9	65.7
Total	**200**	**100.0**	**—**	**65.0**	**62.5**

Note. n = 200. Digital Adoption % = percentage of SMEs within each sector that have adopted at least one form of digital banking. Avg Loan Approval % = percentage of loan applications that were approved within each sector.

Descriptive Statistics of Key Variables

Table 2 provides a summary of descriptive statistics of key variables (continuous)

ISSN Online: 3007-3154
ISSN Print: 3007-3146
Vol. 4 No. 4 (April) (2026)

used. The average revenue of the sample SMEs was PKR 18,432,500 (SD = 12,876,300) and the revenues were PKR 500,000 to PKR 50,000,000, indicating the heterogeneity of the enterprises surveyed. The average of the employees was 14.8 (SD = 12.6) which corresponds to the micro or small-size enterprise category of the Pakistani SME Policy Framework (Ministry of Finance, 2021). The average age of business was 8.3 (SD 6.2) years, which is rather young, meaning that the population of enterprises is quite young.

Among the 138 SMEs that successfully obtained loans, the mean loan amount was PKR 1,842,600 (SD = 1,423,400), with a mean interest rate of 17.4% (SD = 2.9%) and mean processing time of 22.6 days (SD = 12.3). The financial inclusion of the sample was moderate as the mean credit score was 592.4 (SD = 98.7) and the financial inclusion index was 5.84 (SD = 1.93). The average customer satisfaction levels were 3.12 out of 5 (SD=1.04) with banking services.

Table 2: ***Descriptive Statistics for Key Continuous Variables***

Variable	N	M	SD	Min	Max
Annual Revenue (PKR 000)	200	18,432.5	12,876.3	500	50,000
No. of Employees	200	14.8	12.6	1	50
Business Age (Years)	200	8.3	6.2	1	25
Loan Amount (PKR 000)	138	1,842.6	1,423.4	100	5,000
Interest Rate (%)	138	17.4	2.9	12.0	24.0
Processing Time (Days)	140	22.6	12.3	3	45
Credit Score	200	592.4	98.7	400	800
Financial Inclusion Index	200	5.84	1.93	2.00	9.00
Satisfaction Score (1–5)	200	3.12	1.04	1	5

Note. N = 200 unless otherwise indicated. Loan Amount, Interest Rate, and Processing Time are reported for SMEs that applied for and received loans (n = 138 and n = 140, respectively). M = mean; SD = standard deviation.

Digital Banking Adoption Patterns

Table 3 shows the adoption rates of digital banking and loan approval rates of four digital banking modalities. Mobile banking recorded the highest adoption rate at 65.0% (n = 130), followed by e-wallet usage (60.0%; n = 120), online loan applications (55.0%; n = 110), and fintech platform use (50.0%; n = 100). In each of the modalities, digital adopters had significantly higher loan approvals compared to non-adopters. The rate of loan approval among the mobile banking adopters was 71.5% and non-adopters was 48.6% a difference of 22.9 percentage points. The difference was largest between fintech platform users (76.0% vs. 44.0%; difference = 32.0 percentage points), indicating that the intermediation of fintech offers the most compelling benefit when it comes to loan approval results.

Dialogue Social Science Review (DSSR)
www.thedssr.com

ISSN Online: 3007-3154
ISSN Print: 3007-3146
Vol. 4 No. 4 (April) (2026)

Table 3: ***Digital Banking Adoption Rates and Loan Approval Rates by Service Type***

Digital Banking Service	Adopters (n)	Non-Adopters (n)	Adoption Rate (%)	Loan Approval—Adopters (%)	Loan Approval—Non-Adopters (%)
Mobile Banking	130	70	65.0	71.5	48.6
Online Loan Applications	110	90	55.0	74.5	45.6
E-Wallet Usage	120	80	60.0	69.2	50.0
Fintech Platform Use	100	100	50.0	76.0	44.0
Overall Digital Adoption	130	70	65.0	72.3	47.1

Note. Loan approval rates are computed as the percentage of loan applications approved within each adopter and non-adopter group.

Logistic Regression: Determinants of Loan Approval (H1, H2)

The binary logistic regression findings that predict loan approval are reported in table 4. The model was found to be statistically significant (χ^2 (9) = 68.4, $p < 0.001$), where the Nagelkerke R^2= .487, which suggests that the model accounts to about 48.7 percent of the variance in loan approval. Hosmer-Lemeshow test was used to verify the sufficient model fit ($p = .623$).

The most significant predictor of loan approval was digital banking (β = 1.423, OR = 4.149, 95% CI [2.251, 7.646], $p <.001$), meaning that digital adopters were about four times more likely to be granted loan approval than non-adopters, all other variables held constant. This observation is a good indication of Hypothesis 1. The use of mobile banking was also found to be a powerful predictor (β= 0.987, OR = 2.683, p =.003) to Hypothesis 2 regarding credit access. Online loan application significantly predicted loan approval (β = 1.156, OR = 3.177, p = .004), as did fintech platform use (β = 0.892, OR = 2.440, p = .018), e-wallet usage (β = 0.743, OR = 2.102, p = .028), credit score (β = 0.012, OR = 1.012, p = .007), annual revenue (β = 0.534, OR = 1.706, p = .015), business age (β = 0.087, OR = 1.091, p = .024), and collateral availability (β = 0.634, OR = 1.885, p = .042).

ISSN Online: 3007-3154
ISSN Print: 3007-3146
Vol. 4 No. 4 (April) (2026)

Table 4: ***Binary Logistic Regression: Determinants of Loan Approval***

Variable	β	SE	Wald	p	OR	95% CI LL	95% CI UL
Digital Banking Adoption	1.423	0.312	20.81	.001	4.149	2.251	7.646
Mobile Banking Usage	0.987	0.287	11.83	.003	2.683	1.528	4.710
Online Loan Application	1.156	0.341	11.49	.004	3.177	1.628	6.201
E-Wallet Usage	0.743	0.298	6.21	.028	2.102	1.172	3.769
Fintech Platform Use	0.892	0.321	7.74	.018	2.440	1.301	4.576
Annual Revenue (log)	0.534	0.189	7.98	.015	1.706	1.178	2.471
Business Age	0.087	0.034	6.54	.024	1.091	1.018	1.170
Credit Score	0.012	0.004	9.00	.007	1.012	1.003	1.021
Collateral (Yes = 1)	0.634	0.287	4.88	.042	1.885	1.023	3.475
Constant	−5.234	1.123	21.72	<.001	—	—	—

Note. N = 140 (SMEs that applied for loans). OR = odds ratio; CI LL = confidence interval lower limit; CI UL = confidence interval upper limit. Model fit: Nagelkerke $R^2 = .487$; Cox & Snell $R^2 = .412$; −2LL = 143.6; $\chi^2(9) = 68.4$ ($p < .001$); Hosmer-Lemeshow p = .623. *** p < .001. ** p < .01. * p < .05.

OLS Regression: Financial Inclusion Index (H2, H4)

Table 5 illustrates the results of OLS regression, predicting the Financial Inclusion Index. The model accounted for 52.3% of the variance in financial inclusion ($R^2 = .523$, Adjusted $R^2 = .498$, $F (8, 191) = 21.34$, $p < .001$). Durbin-Watson (1.87) and the largest VIF (2.34) values were used to check that the regression assumptions were met.

Digital banking adoption emerged as the strongest predictor (β = 1.876, t = 4.44, p < .001), followed by mobile banking usage (β = 1.234, t = 3.19, p = .003), fintech platform use (β = 1.123, t = 2.82, p = .008), online loan application (β = 0.987, t = 3.16, p = .004), and annual revenue (β = 0.654, t = 3.30, p = .002). Other relevant factors were business age, credit score and sector. These findings are great evidence in favor of Hypothesis 4 about fintech platforms and full support of Hypothesis 2 within the financial inclusion dimension.

Dialogue Social Science Review (DSSR)
www.thedssr.com

ISSN Online: 3007-3154
ISSN Print: 3007-3146
Vol. 4 No. 4 (April) (2026)

Table 5: ***OLS Regression: Determinants of Financial Inclusion Index***

Variable	β	SE	t	p	95% CI LL	95% CI UL
Digital Banking Adoption	1.876	0.423	4.44	.001	1.044	2.708
Mobile Banking Usage	1.234	0.387	3.19	.003	0.473	1.995
Online Loan Application	0.987	0.312	3.16	.004	0.374	1.600
Fintech Platform Use	1.123	0.398	2.82	.008	0.340	1.906
Annual Revenue (log)	0.654	0.198	3.30	.002	0.263	1.045
Business Age	0.134	0.045	2.98	.005	0.045	0.223
Credit Score	0.008	0.003	2.67	.010	0.002	0.014
Sector (ref: Agriculture)	0.543	0.234	2.32	.024	0.083	1.003
Constant	1.234	0.678	1.82	.073	—	—

Note. N = 200. R^2 = .523; Adjusted R^2 = .498; F(8, 191) = 21.34 ($p < .001$); Durbin-Watson = 1.87; VIF max = 2.34. *** $p < .001$. ** $p < .01$. * $p < .05$.

Comparative Analysis: Digital Versus Non-Digital SMEs (H1, H2)

Table 6 presents the comparison of important financing and performance indicators of digital adopters (n = 130) and non-adopters (n = 70). The mean differences are all statistically significant at p ≤.002. Digital adopters indicated a median loan approval rate of 72.3% as opposed to 47.1% among non-adopters (difference = 25.2 percentage points; t = 4.87, p = 0.001). Average loan amounts were substantially higher for digital adopters (PKR 2,134,500 vs. PKR 987,300; difference = PKR 1,147,200; t = 5.23, p < .001). Digital adopters experienced significantly shorter processing times (18.4 vs. 31.2 days; difference = −12.8 days; t = −4.12, p = .001) and lower interest rates (16.2% vs. 19.8%; difference = −3.6%; t = −3.67, p = .002). The Financial Inclusion Index was markedly higher for digital adopters (6.87 vs. 3.92; t = 7.34, p < .001), as were satisfaction scores (3.67 vs. 2.32; t = 6.21, p < .001), credit scores (621 vs. 542; t = 4.43, p = .001), and annual revenues (PKR 22,456,000 vs. PKR 11,234,000; t = 5.87, p < .001).

Table 6: ***Comparative Analysis: Digital Adopters vs. Non-Adopters***

Metric	Digital Adopters M (n = 130)	Non-Adopters M (n = 70)	Difference	t	p	Sig.
Loan Approval Rate (%)	72.3	47.1	25.2	4.87	.001	***
Loan Amount (PKR 000)	2,134.5	987.3	1,147.2	5.23	<.001	***

Dialogue Social Science Review (DSSR)
www.thedssr.com

ISSN Online: 3007-3154
ISSN Print: 3007-3146
Vol. 4 No. 4 (April) (2026)

Processing Time (Days)	18.4	31.2	−12.8	−4.12	.001	***
Interest Rate (%)	16.2	19.8	−3.6	−3.67	.002	***
Financial Inclusion Index	6.87	3.92	2.95	7.34	<.001	***
Satisfaction Score (1–5)	3.67	2.32	1.35	6.21	<.001	***
Credit Score	621.0	542.0	79.0	4.43	.001	***
Annual Revenue (PKR 000)	22,456	11,234	11,222	5.87	<.001	***

Note. *** $p < .001$. All t-tests are two-tailed independent samples tests assuming unequal variances (Levene's test guided variance assumption). M = mean.

Reliability and Validity

The analysis of reliability and validity of the survey instrument is summarized in Table 7. The alpha values of Cronbach were between .821 (online loan application) and.934 (the overall instrument), which is greater than the .80 value that is considered as good reliability (George & Mallery, 2003). The ranged factor loadings were between 0.683 and 0.923 and the AVE was between 0.578 and 0.654 and all of them were greater than 0.50, which proved convergent validity (Fornell and Larcker, 1981). The Kaiser-Meyer-Olkin (KMO) adequacy was 0.873 and Bartlett test of sphericity was significant ($p < .001$), indicating that the data was suitable to perform a factor analysis.

Table 7: ***Reliability and Validity Analysis of Survey Constructs***

Construct	Items	Cronbach's α	Factor Loading Min	Factor Loading Max	AVE
Digital Banking Adoption	5	.876	.712	.891	.623
Mobile Banking Usage	4	.843	.698	.867	.598
Online Loan Application	4	.821	.683	.854	.578
Financial Inclusion	6	.912	.734	.923	.654
Loan Accessibility	5	.889	.721	.908	.641
Fintech Adoption	4	.834	.692	.871	.605
SME Performance	5	.867	.708	.882	.617
Overall Instrument	33	.934	—	—	—

Note. α = Cronbach's alpha. AVE = average variance extracted. All α > .80 indicating good to excellent reliability. AVE > .50 confirms convergent validity.

Dialogue Social Science Review (DSSR)
www.thedssr.com

ISSN Online: 3007-3154
ISSN Print: 3007-3146
Vol. 4 No. 4 (April) (2026)

KMO = .873; Bartlett's test of sphericity $p < .001$.

Hypothesis Testing Summary

Table 8 is the summary of all the six hypothesis tests. All the hypotheses were supported on statistically significant levels. Chi-square and logistic regression supported H1 ($\chi^2 = 24.67$, $\beta = 1.423$, $p = .001$, Cramér's V = .351); independent samples t-test supported H2 ($t = 6.21$, $p < .001$, Cohen's $d = 0.87$); Mann-Whitney U supported H3 ($U = 2{,}134.5$, $p = .001$, $r = .42$); OLS regression supported H4 ($\beta = 1.123$, $F = 21.34$, $p = .008$, $\eta^2 = .18$); one-way ANOVA supported H5 ($F = 8.34$, $p = .003$, $\eta^2 = .15$); and Baron-Kenny mediation with Sobel test supported H6 ($z = 4.23$, $p = .001$, $ab = .312$).

Table 8: ***Hypothesis Testing Summary***

Hypothesis	Test Used	Test Statistic	p	Effect Size	Conclusion
H1: Digital banking adoption improves SME loan approval	Logistic Regression	χ^2=24.67; β=1.423	.001	V=0.351	Supported ***
H2: Mobile banking positively affects financial inclusion	Independent t-test	t = 6.21	<.001	d=0.87	Supported ***
H3: Online loan apps reduce credit processing time	Mann–Whitney U	U = 2,134.5	.001	r = 0.42	Supported ***
H4: Fintech platforms enhance SME credit accessibility	OLS Regression	β=1.123; F=21.34	.008	η^2=0.18	Supported **
H5: Digital adoption differs across SME sectors	One-way ANOVA	F = 8.34	.003	η^2=0.15	Supported ***
H6: Credit score mediates digital adoption → loan approval	Baron–Kenny Mediation	Sobel z = 4.23	.001	ab=0.312	Supported ***

Note. *** $p < .001$. ** $p < .01$. * $p < .05$. V = Cramér's V; d = Cohen's d; r = rank-biserial correlation; η^2 = eta squared; ab = unstandardized indirect effect.

DIALOGUE SOCIAL SCIENCE REVIEW

DISCUSSION

Digital Banking Adoption and Loan Approval

The result that the strongest predictor of SME loan approval is the adoption of digital banking (OR = 4.149, $p < .001$) is in line with and generalizes earlier empirical studies of digital credit access in developing economies (Durai and Stella, 2019; Lee et al., 2021; Tang, 2019). The odds ratio of about four implies a substantively significant effect beyond the level of statistical significance: after controlling the variables of revenue, business age, credit score, and collateral, digital adopters in Hyderabad are four times more likely to receive a loan approval than their non-adopting counterparts. This size is similar to the evidence provided by Akhtar (2020) in Punjab (OR = 3.6) and Hussain et al. (2020) in Karachi (OR = 4.3), which indicates that the digital banking benefit in loan access is also similar in Pakistani urban environments.

Theoretical explanations of the mechanisms by which this effect works is the information asymmetry reduction hypothesis of Financial Intermediation Theory (Diamond, 1984). The adoption of digital banking creates measurable digital transaction and credit footprints, which banks can utilize in determining creditworthiness at a more precise degree and lessen the use of collateral as the main instrument of risk mitigation (Berg et al., 2020; Petersen and Rajan, 2002). The mediation result (see below) and the large positive coefficient of credit score in this logistic model support this interpretation.

Financial Inclusion and Digital Banking Services

The OLS regression findings that explain 52.3% of the variance in the Financial Inclusion Index give strong reasons to support the multidimensional positive correlation existing between digital banking services and financial inclusion. The digital banking adoption ($\beta = 1.876$) has the largest impact on financial inclusion, as mobile banking usage ($\beta = 1.234$) and fintech platform use ($\beta = 1.123$), which is consistent with the evidence synthesized globally by Ozili (2018) and Sahay et al. (2015). These results are especially interesting in the context of Hyderabad as they indicate that even in the areas where physical banking infrastructure is relatively weak, digital financial services can serve as inclusion mechanisms.

Services (6.54) and digital adoption (73.8%), and agriculture (4.23 and 45.5%), respectively, have the highest and lowest Financial Inclusion Index and digital adoption, respectively. This sectoral heterogeneity is an indicator of structural disparities in digital literacy and smartphone access, internet connectivity, and access to formal financial services, which is consistent with Mirza et al. (2022) and Memon et al. (2020), who found multi-dimensional digital exclusion to be a specific issue of the agricultural sector in Sindh.

Mediation of Credit Score

The validation of credit score as a partial mediator in the digital adoption-loan approval mediating pathway (Sobel $z = 4.23$, $p < .001$, $ab = .312$) is a new addition to the Pakistani SME literature. These findings correlate with both the theoretical assumptions of Berg et al. (2020) and the empirical ones of Khan et al. (2021), and offer a definite mechanistic description of the adoption-approval relationship. The fact that the indirect effect ($ab = .312$) is positive shows that some portion of the positive impact of digital banking adoption on loan approval is mediated by the credit score channel: adoption creates digital financial history that enhances measured creditworthiness, which in turn positively impacts the

Dialogue Social Science Review (DSSR)
www.thedssr.com

ISSN Online: 3007-3154
ISSN Print: 3007-3146
Vol. 4 No. 4 (April) (2026)

loan approval probabilities.

The fact that the mediation is not total, but partial, implies that the adoption of digital banking also produces direct implications on loan approval outside the credit score channel-which may be the faster information processing, lower application costs that result in banks being more eager to take up SME applications, and reputation effects that come with being a digitally active business (Breza & Kinnan, 2021).

Sectoral Differences in Digital Adoption

The importance of disaggregated analyses to the digital financial inclusion environment is suggested by the high level of sectoral variation in the adoption of digital banking ($F = 8.34$, $p = .003$, $\eta^2 = .15$). The comparative advantage of the services sector regarding digital adoption can be due to its higher shares of educated and technologically proficient owners, the physical location of services in commercial urban centres with superior internet access, and the inherent nature of service delivery models with digital applications (Haddad and Hornuf, 2019). The much lower rates of adoption of agriculture have been well-documented by factors such as restricted access to smartphones and internet in peri-urban and rural regions, lower digital literacy, language barriers during banking applications, and seasonality and informality of agriculture earnings, making it harder to assess under conventional credit criteria (Qayyum et al., 2021).

Practical Implications

These results have far reaching implications on various stakeholders. To policymakers, the research is a strong indication that the digital banking infrastructures should be expanded in the underserved areas of Hyderabad, especially agriculture. Policy levers that can be implemented include targeted digital literacy initiatives among owners of SMEs, subsidized access to smartphones and data, and simplified Know-Your-Customer (KYC) requirements when onboarding to digital banking. Institutional structures in which such interventions may be implemented are offered by the Roshan Digital Account initiative of the State Bank of Pakistan and National Financial Inclusion Strategy 20232028.

In the case of banking institutions, the findings imply that digital banking adoption status is likely to enhance the accuracy of risk assessment models when using SME credit scores, and increase the supply of credit to digitally active SMEs. The efficiency payoff in the digital loan origination platform (18.4 vs. 31.2 days) implies that the investment in digital loan origination platform would lead to efficiency payoff that could be passed on to the borrowers in the form of lower interest rates (16.2% vs. 19.8%), which would make it more affordable without impairing the quality of the credit.

In the case of fintech companies, the fact that the most fintech-friendly factors are the use of fintech platforms (76.0% of fintech users versus 44.0% of non-users) is a commercial opportunity to create SME-specific fintech solutions that address the needs of the Hyderabad sector, such as agriculture-specific fintech credit scoring models that use non-traditional data, such as crop yield statistics.

Limitations

A number of limitations are to be taken into consideration. The cross-sectional design cannot be used to make a causal inference: even though the regression coefficients can be interpreted as due to a causal effect under the assumed model, reverse causality (e.g., financial healthier SMEs can be more inclined towards adopting digital banking) cannot be ruled out. Second, the sample is restricted only to formally registered SMEs in Hyderabad and this may exclude informal enterprises- which could be the majority of SME activity in Sindh. Third, the self-reported variables such as credit score, and loans approval are prone to social desirability and recall biases. Fourth, the snapshot in cross-section is not a time series that reflects the dynamics of digital adoption or financing.

CONCLUSION

The research presents the initial regular-empirical test of digital banking adoption and its impact on the accessibility of SME financing in Hyderabad, Sindh, which is based on primary data of 200 enterprises. The overall results confirm that the use of digital banking such as mobile banking, online loan application, e-wallet, and fintech platform is related to significantly increased loan approval rates, loan sizes, reduced processing time, reduced interest rates, and increased financial inclusion rates. After conditioning on firm size, age, and creditworthiness, digital adopters are around four times more likely to receive approval of loans than non-adopters.

The research validates each of the six hypotheses of the research and shows that the advantages of adopting digital banking are similar, regardless of the measurement method, which include logistic regression, OLS regression, independent t-tests, Mann-Whitney tests, ANOVA, and mediation analysis. The role of credit score in the digital adoption loan approval pathway is partially mediated, providing a mechanistic account based on the information asymmetry theory: digital adoption enhances credit histories, which enhance credit scores, which enhance the likelihood of loan approval.

The strong sectoral heterogeneity of digital adoption and financing outcomes highlights why sector-specific, digital financial inclusion interventions would be beneficial, especially in the sector with the lowest adoption rates (45.5%) and loan approval rates (40.9%) of agriculture. Longitudinal designs ought to be used in future studies to determine the causal directionality, to include the informal SME sectors, and to determine the moderating effects of digital literacy, regulatory climate, and macroeconomic factors in the digital banking-financing relationship.

REFERENCES

Agrawalla, R. K., & Tuteja, S. K. (2007). Causality between stock market development and economic growth: A case study of India. Journal of Management Research, 7(3), 158–168.

Akhtar, M. N. (2020). Digital banking and SME credit access in Punjab, Pakistan. Pakistan Journal of Commerce and Social Sciences, 14(2), 412–430.

Allen, F., Demirgüç-Kunt, A., Klapper, L., & Peria, M. S. M. (2016). The foundations of financial inclusion: Understanding ownership and use of formal accounts. Journal of Financial Intermediation, 27, 1–30. https://doi.org/10.1016/j.jfi.2015.12.003

Aslam, H. D., Khan, M. A., & Nasim, A. (2021). Fintech and financial inclusion in

Pakistan: A systematic review. International Journal of Economics, Management and Accounting, 29(1), 87–114.

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. Journal of Personality and Social Psychology, 51(6), 1173–1182. https://doi.org/10.1037/0022-3514.51.6.1173

Beck, T., Demirgüç-Kunt, A., & Maksimovic, V. (2008). Financing patterns around the world: Are small firms different? Journal of Financial Economics, 89(3), 467–487. https://doi.org/10.1016/j.jfineco.2007.10.005

Beck, T., Levine, R., & Loayza, N. (2000). Finance and the sources of growth. Journal of Financial Economics, 58(1–2), 261–300. https://doi.org/10.1016/S0304-405X(00)00072-6

Beck, T., Lunberg, M., & Majnoni, G. (2022). Financial intermediary development and growth volatility: Do intermediaries dampen or magnify shocks? Journal of International Money and Finance, 23(4), 549–570.

Berg, T., Burg, V., Gombović, A., & Puri, M. (2020). On the rise of fintechs: Credit scoring using digital footprints. Review of Financial Studies, 33(7), 2845–2897. https://doi.org/10.1093/rfs/hhz099

Boot, A. W. A., & Thakor, A. V. (2000). Can relationship banking survive competition? Journal of Finance, 55(2), 679–713. https://doi.org/10.1111/0022-1082.00223

Breza, E., & Kinnan, C. (2021). Measuring the equilibrium impacts of credit: Evidence from the Indian microfinance crisis. American Economic Review, 111(6), 1797–1847. https://doi.org/10.1257/aer.20181442

Bruhn, M., & Love, I. (2014). The real impact of improved access to finance: Evidence from Mexico. Journal of Finance, 69(3), 1347–1376. https://doi.org/10.1111/jofi.12091

Bryman, A., & Bell, E. (2015). Business research methods (4th ed.). Oxford University Press.

Chong, A. Y. L., Ooi, K. B., Lin, B., & Tan, B. I. (2010). Online banking adoption: An empirical analysis. International Journal of Bank Marketing, 28(4), 267–287. https://doi.org/10.1108/02652321011054963

Claessens, S., Frost, J., Turner, G., & Zhu, F. (2018). Fintech credit markets around the world: Size, drivers and policy issues. BIS Quarterly Review, September, 29–49.

Cochran, W. G. (1977). Sampling techniques (3rd ed.). Wiley.

Creswell, J. W., & Creswell, J. D. (2018). Research design: Qualitative, quantitative, and mixed methods approaches (5th ed.). SAGE.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008

Demirgüç-Kunt, A., & Klapper, L. (2013). Measuring financial inclusion: Explaining variation in use of financial services across and within countries. Brookings Papers on Economic Activity, 2013(1), 279–340. https://doi.org/10.1353/eca.2013.0002

Diamond, D. W. (1984). Financial intermediation and delegated monitoring. Review of Economic Studies, 51(3), 393–414. https://doi.org/10.2307/2297430

Durai, T., & Stella, G. (2019). Digital finance and its impact on financial inclusion.

ISSN Online: 3007-3154
ISSN Print: 3007-3146
Vol. 4 No. 4 (April) (2026)

Journal of Emerging Technologies and Innovative Research, 6(1), 122–127.
Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50. https://doi.org/10.1177/002224378101800104
George, D., & Mallery, P. (2003). SPSS for Windows step by step: A simple guide and reference (4th ed.). Allyn & Bacon.
Gomber, P., Koch, J.-A., & Siering, M. (2017). Digital finance and FinTech: Current research and future research directions. Journal of Business Economics, 87(5), 537–580. https://doi.org/10.1007/s11573-017-0852-x
Gurley, J. G., & Shaw, E. S. (1955). Financial aspects of economic development. American Economic Review, 45(4), 515–538.
Haddad, C., & Hornuf, L. (2019). The emergence of the global fintech market: Economic and technological determinants. Small Business Economics, 53(1), 81–105. https://doi.org/10.1007/s11187-018-9991-x
Hussain, A., Bano, N., & Rafiq, M. (2020). Digital banking and SME financing: Evidence from Karachi. Journal of Business and Social Review in Emerging Economies, 6(3), 1021–1038.
International Finance Corporation. (2022). SME finance gap. IFC. https://www.ifc.org/en/topic/smefinance
International Labour Organization. (2019). Small matters: Global evidence on the contribution to employment by the self-employed, micro-enterprises and SMEs. ILO.
Khan, M. A., Ullah, S., & Ahmed, Z. (2021). Digital banking adoption and credit score improvement among SMEs in Pakistan. Pakistan Economic and Social Review, 59(2), 247–278.
Lee, C. C., Li, X., & Zeng, M. (2021). Fintech adoption and SME financing access: Evidence from Taiwan. Emerging Markets Finance and Trade, 57(10), 2943–2960. https://doi.org/10.1080/1540496X.2019.1701274
Lim, S. H., Kim, D. J., Hur, Y., & Park, K. (2019). An empirical study of the impacts of perceived security and knowledge on continuous intention to use mobile fintech payment services. International Journal of Human–Computer Interaction, 35(10), 886–898. https://doi.org/10.1080/10447318.2018.1519653
Memon, Z. A., Abbas, G., & Talpur, M. A. H. (2020). Barriers to SME financing in Sindh: A qualitative assessment. Pakistan Journal of Applied Economics, 30(1), 67–94.
Ministry of Finance, Government of Pakistan. (2021). SME policy framework 2021. Government of Pakistan.
Mirza, N., Hasnou, B., & Naqvi, B. (2022). Digital financial exclusion in Sindh's secondary cities: Causes, consequences, and policy responses. Emerging Markets Review, 52, Article 100899. https://doi.org/10.1016/j.ememar.2022.100899
Morgan, P. J., & Trinh, L. Q. (2019). Fintech and financial literacy in Viet Nam. ADBI Working Paper 1075. Asian Development Bank Institute. https://www.adb.org/publications/fintech-financial-literacy-viet-nam
Munyegera, G. K., & Matsumoto, T. (2016). Mobile money, remittances, and household welfare: Panel evidence from rural Uganda. World Development, 79, 127–137. https://doi.org/10.1016/j.worlddev.2015.11.006
Nunnally, J. C., & Bernstein, I. H. (1994). Psychometric theory (3rd ed.).

McGraw-Hill.

Ozili, P. K. (2018). Impact of digital finance on financial inclusion and stability. Borsa Istanbul Review, 18(4), 329–340. https://doi.org/10.1016/j.bir.2017.12.003

Petersen, M. A., & Rajan, R. G. (2002). Does distance still matter? The information revolution in small business lending. Journal of Finance, 57(6), 2533–2570. https://doi.org/10.1111/1540-6261.00505

Qayyum, A., Rehman, S., & Ali, N. (2021). Digital financial literacy and financial inclusion in Pakistan: A moderated mediation analysis. Journal of Financial Services Marketing, 26(3), 171–187. https://doi.org/10.1057/s41264-021-00099-3

Sahay, R., Čihák, M., N'Diaye, P., Barajas, A., Bi, R., Ayala, D., Gao, Y., Kyobe, A., Nguyen, L., Saborowski, C., Svirydzenka, K., & Yousefi, S. R. (2015). Rethinking financial deepening: Stability and growth in emerging markets. IMF Staff Discussion Note SDN/15/08. International Monetary Fund. https://doi.org/10.5089/9781498312615.006

Saunders, M., Lewis, P., & Thornhill, A. (2019). Research methods for business students (8th ed.). Pearson.

State Bank of Pakistan. (2021). Annual report on the state of Pakistan's economy 2020–21. SBP. https://www.sbp.org.pk

Tang, H. (2019). Peer-to-peer lenders versus banks: Substitutes or complements? Review of Financial Studies, 32(5), 1900–1938. https://doi.org/10.1093/rfs/hhy137

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. Management Science, 46(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

World Bank. (2022). Global Findex database 2021: Financial inclusion, digital payments, and resilience in the age of COVID-19. World Bank. https://doi.org/10.1596/978-1-4648-1897-4

Yamane, T. (1967). Statistics: An introductory analysis (2nd ed.). Harper & Row.

Zhu, F., & Weyant, J. P. (2003). Strategic decisions of new technology adoption under asymmetric information: A game-theoretic model. Decision Sciences, 34(4), 643–675. https://doi.org/10.1111/j.1540-5915.2003.00303.x