Technological advancement in microfinance lending: Transforming access and efficiency in India

Loans/Microfinance from NBFCs

12th June 2023

MSC
MicroSave Consulting

Models for digital lending from NBFCs/MFIs/FinTechs

MSC
MicroSave Consulting

Process of understanding of credit worthiness – 5C analysis

With the digitization of income for MSMEs, the availability of surrogate data such as telecom, utility, and social media, combined with psychometric analysis to evaluate ability is ushering in new models of credit-worthiness

Capital

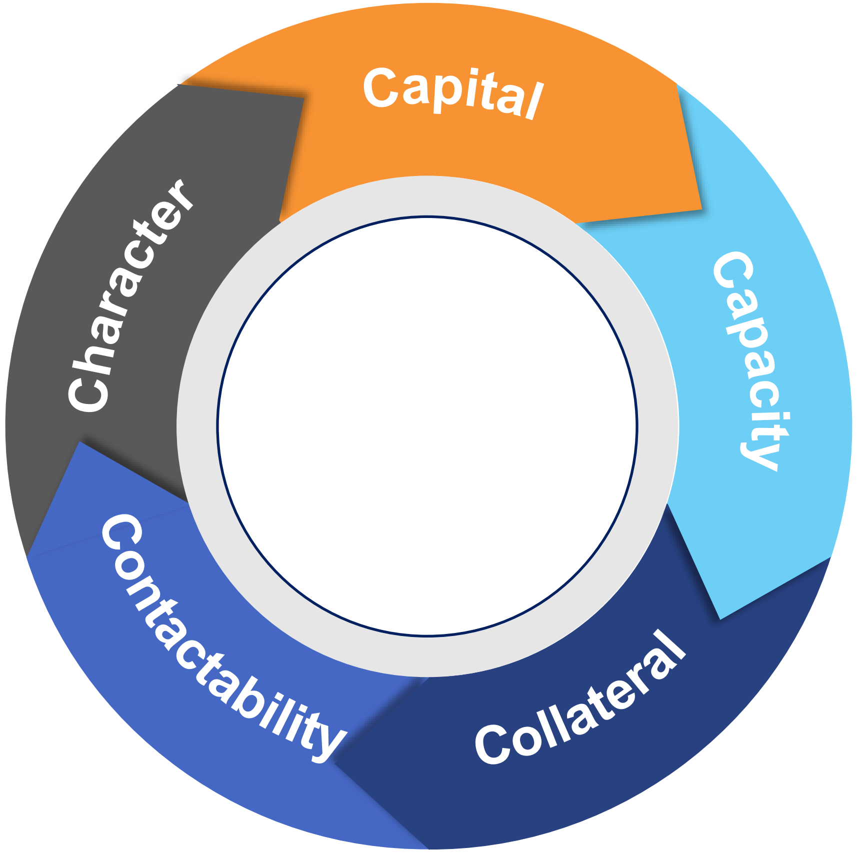
- Sources of income (consistent / one-time. stability / volatility, cash/accounting, surrogates / transactional)
- Use of income

Character

- Past behavior based on alternative data
- References Checks
- Verification

Contactability

- Phone number and address (linked to eKYC)
- GPS locators for residential and business address



Capacity

- Bureau and Bank Statement
- GST / Income tax returns
- Assessment of other pending loans (should not have an existing business loan)
- Assessment of other family commitments (expenses made for children / dependent parents,, secondary business, assets owned etc.)

Collateral

- Secured loan: Collateral based on loan size
- Unsecured loan: Social Collateral though Guarantors & References

Factors applicable for consumer and MSME lending

Factors applicable for MSME lending only

New age risk assessment using data analytics

Lenders are moving from traditional means of underwriting and using tech-driven, open-source information and proxy indicators to assess the financial well-being of prospective borrower. Use of AI/ML is key in analyze and codify risk, predict severity

Financial Data

Financial information
Salary slips, balance sheet, P&L, Transaction data, Bank statement

Bureau data
CIBIL, Experian, Equifax, CRILIC

Tax data
GSTN, Income tax, 26AS, TIN

Payment Data
UPI, e-commerce, PoS

Personal & business data

Demographic
PAN, Aadhar, Triangulation of consent architecture

Utility data
Electricity, telecom, internet, gas

Publically available data
Negative news, legal, merger & acquisition, stocks, interviews

Informal sources

Internet and social data
Neuroscience and behavior

Mobile data
Call history, app usage, app catalogue, system information

Enablers

Tech advancements
Increased availability and access to data in digital form
Consent based access
Capacity for instant triangulation
Advancement in AI/ML

Types of data used in credit scoring for MSMEs

Credit providers used different types of structured data to build scores. In the recent past, there has been a shift to more unstructured data

1. Payment history: Credit providers use records on current and past credit accounts to build scores. Financial institutions use data from as far back as seven years to build payment history and calculate scores.

2. Public records: Sub-judice matters such as bankruptcies, liquidations, and adverse judgments may indicate potential troubles.

3. Mobile data: Mobile data may provide granular information and insights into consumer behavior. For example, the number of frequent contacts indicates an extensive network. Similarly, geolocation data and where borrowers frequent also show creditworthiness.

4. Utility data: Data from utility providers such as electricity, water, post, telephone, and proof that the user regularly pays utility bills indicate stability.

5. Commercial data: Financial statement information, cashflow information, management information, and operational information may indicate businesses' creditworthiness. Consistent financial results demonstrate the business is healthy and credit-worthy.

6. Macroeconomic data: A change in the macroeconomic conditions, for example, high inflation, unemployment, and adverse effects of the COVID-19 pandemic in a region, may impact the credit scores of consumers and businesses in that region.

There are some digital lenders which are banking of MSMEs

Loan Type	Providers Name	Business Model D: Digital only D + P: Digital and Physical	Credit Range (in INR)	Rate of Interest (%)	Repayment Time (Days)	Volumes L: loan disbursed (USD) B: borrower base	Turn-around time
Personal	INDIALENDS	D	15000-500,000	10.75-35	365-2,190	L: 201 million	1 hour
	Money View LOANS	D	10,000-500,000	1.33-No Upper Limit	Flexible-1825	B: 10 million	24 hours
	zest EMI FOR EVERYONE	D	75,000-1,60,00,000	30	185-730	B: 6 million	8 hours
Business	LENDINGKART	D + P	500,000-2,00,00,000	15-27	30-365	L: 210 million B: 89,000 MSMEs	24-72 hours
Term loan	CAPITAL FLOAT	D	500,000-5,00,00,000	18-24	30-1095	L: 1.15 billion B: 0.5 mn MSMEs	72 hours
	indifi	D	N/A-500,000	16-24	Variable-1095	B: 25,000 MSMEs	24 hours
Supply chain finance	NEOGROWTH Lending simplified. Growth amplified.	D + P	10,00,000-15,00,000	Variable	N/A-730	L: 6 billion B: 17,000 MSMEs	3-5 days
Retail	slice	D	N/A	0-20	N/A	B: 0.25 million	Up to 1 hour
	VOTE FOR CASH Need it . Get it !	D	N/A-10,00,000	36-108	1-30	N/A	Within 24 hours
	KBNBFC	D	1500-35,000	Variable	90-365	L: 576 million B: 2.2 million	24 hours

Judgmental Credit Scoring Tool – XYZ NBFC

Category	Component	Finding
Borrower	Age of borrower	> 25, <=40 years
	Experience of borrower	>5 and =<8 years
	Experience of borrower in current business	>5 and =<8 years
	Credit Bureau History	Has taken at least 1 loan in the past, and never delayed in repayments
	House ownership	Owned by Children / Parent/ Grand parents/ Parent-in-laws
	Banking transactions	Regular (at least four transactions per month)
	House electricity bill payments	Latest bill paid on or before time
	Business electricity bill payments	Latest bill paid on or before time
Business	Sector	Retail
	Business premise ownership	Rented and operating at same location for 1-2.9 years
	Location	Services / Trading - Front and easy access in a small market area Manufacturing - Medium Approachability
	Level of formalization	Registered with Municipality, Has TAN number, Files IT Returns for business
	Management	Self + family members
	Purpose of Loan	Fixed asset financing
Capacity	Debt service coverage ratio (Average net monthly cashflow / Installment amount)	2.0-2.9
	Total savings percentage against loan amount (Family savings can be formal / informal - bank balance/ RD/ FD/endowment/NSC, etc.)	Formal savings, >25%, <=50% of loan amount
Capital	Alternate verifiable sources of income compared to installment	50-79%

Annex

Creating real value: How digital credit impacts MSMEs involved in delivery of services

1. SMV Green Solutions offers affordable, clean and safe mobility in the last mile transportation

2. SMV's vision is to upgrade existing 10 million manual rickshaw and trolley pullers to electronic rickshaws thus eliminating the drudgery of cycle rickshaw pulling.

3. SMV collaborated with Avanti finance, that has created an opportunity for these rickshaw pullers to access timely credit at a competitive rate.

4. Frictionless digital platform has made it possible paperless loan application and approval access credit. It has further enabled the drivers to avoid the opportunity cost entailed in making multiple physical visits to other credit providers for documentation & verification.

SMV Greens & Avanti finance, Uttar Pradesh, India

Creating real value: Fintech have the appetite and attitude to reach out to MSME categories perceived as risky by the banks

1. Chandra took a group loan from Sub-K. Chandra quadrupled her store inventory (stock) value from USD 70 to USD 280. Then she planned to expand her store to make room for increased inventory.

2. Sub-k executed the process seamlessly through its SARTHI fintech platform.

3. SARTHI offers products like MSME credit, digital microloans, and health insurance that customers can access on their own mobile devices or with assistance from Sub-K's staff and agents.

4. SARTHI is integrated with multiple banks and third-party partners to provide customers with a wide variety of products and payment choices and quick application processing

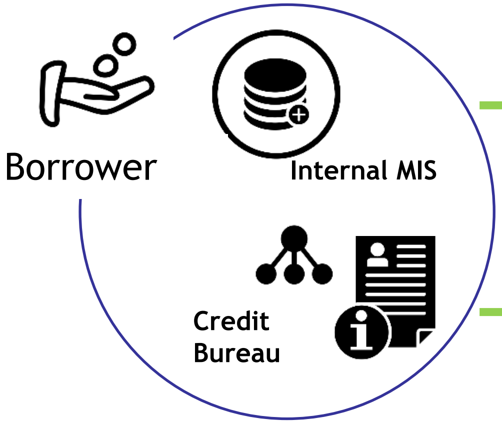
Chandra & SARTHI (Sub – K finance), India

Credit Scoring

Types of Credit Scoring Models

Statistical Credit Scoring

Past Data of the applicant from internal and external sources is used to identify characteristics that help predict the probability of repayment



Binary Logistic Regression

identifies

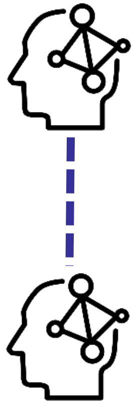
Characteristic 1/ weight 1

Characteristic 2/ weight 2

Characteristic *n*/ weight *n*

Probability to Repay

Judgmental Credit Scoring



Experts use their past knowledge

and judgment to identify

Characteristic 1/ weight 1

Characteristic 2/ weight 2

Characteristic *n*/ weight *n*

Probability to Repay

Sector based experts along with the support of the organisation identify characteristics and their weights to help predict the probability of repayment

Statistical Credit Scoring Tool for an NBFC partner

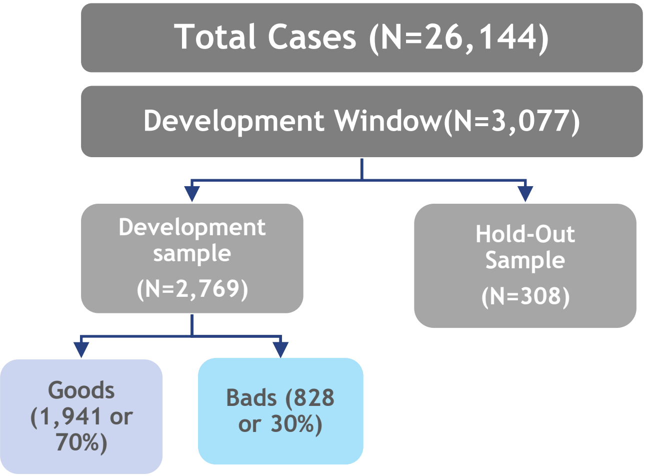
About the Model Development Window

Minimum performance window needed for a loan cycle to be used as a part of the development sample – 6 months

Performance Definition
- Bad Definition: Ever 90+ DPD or Written-off
- Indeterminate: Ever 60 to 89 DPD
- Good Definition: 0 or less then 59 DPD

Resulting development sample includes loan cases from Jan '14 to Mar '16.

Max loan size of past loans: up to INR 1 lakh



Model Parameters

Values	Weightage	Score
Credit Bureau: Disbursed Loan Amount (Non-own)		
The total disbursed value of any active loan issued by a financial institution other than Sonata		
Missing	0	130
<= 0	3.514	231
1 - 15000	0.560	146
15001 - 30000	1.068	160
>=30001	2.201	193
Credit Bureau: Number of Closed Accounts Non-Written Off		
Number of loans successfully paid off in the past by the applicant		
Missing	0.000	130
0	0.700	150
1	0.683	149
>=2	0.922	156
Total Installment		
Installment value of the loan amount requested	0.350	
<= 1650	0.350	140
1651 - 1900	0.700	150
1901 - 2450	1.050	160
2451+	1.400	170
Net Business Cash Flow		
Business Income minus Business Expense		
<=10270	0.188	135
10271 - 11400	0.377	140
11401 - 13600	0.565	146
>=13601	0.753	151
Total Income (regorup 3)		
Sum of business and household income		
<= 11700	0.219	136
11701 - 54240	0.439	142
>=54241	0.658	148
Applicant's Age		
Age of the applicant		
<=28	0.163	134
29-40	0.325	139
>=41	0.488	144

Nuances in the tool building process

Model Strength:

Overall predictive accuracy - 74.2%
Predictive accuracy of goods – 89.8%
Predictive accuracy of bads - 37.7%
GINI – 53.62

Several iterations with client
- **Parameters dropped** due to various reasons
  - **Data equality**, e.g. assets
  - **Strategic reasons**, e.g. caste
- Dropping of parameters allowed for 'age' to become relatively significant

Challenges led to internal iterations
- Model strength function of **small sample size of 'bads'**
- Reduced overall dataset due to **absence of unique identifier** across multiple data sets
- Difficulty in interpreting results due to poor data quality

Since model is based on loans up to INR 1 lakh, the developed score card should be used to assess loan applications for up to INR 1 lakh.

Sectors we work in

Providing impact-oriented business consulting services

- Banking, financial services, and insurance (BFSI)
- Water, sanitation, and hygiene (WASH)
- Government and regulators
- Micro, small, and medium enterprise (MSME)
- Social payments and refugees
- Gender
- Education and skills
- Digital and FinTech
- Agriculture
- Youth
- Climate change and sustainability
- Health and nutrition

Multi-faceted expertise

Advisory that helps you succeed in a rapidly evolving market

- Policy and strategy
- Products and channels
- Research and analytics
- Organizational transformation
- Digital technology and channels
- Catalytic finance
- Design thinking and innovation
- Marketing and communication
- Training
- Government and regulations and policy
- Data Insight

MSC

MSC is recognized as the world's local expert in economic, social and financial inclusion

International financial, social and economic inclusion consulting firm with 25+ years of experience

>200 staff in 10 offices around the world

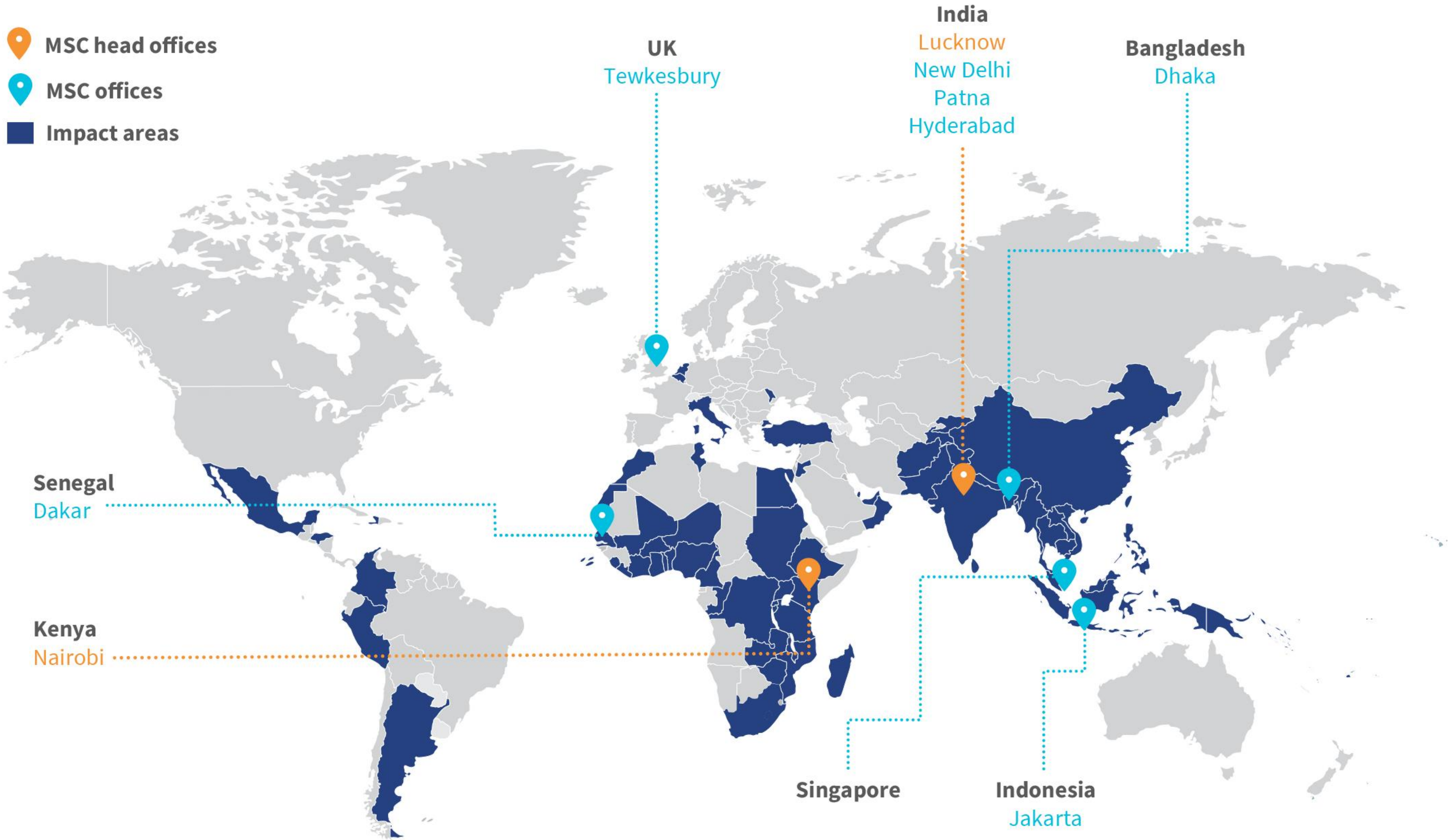
Projects in ~68 developing countries

Our impact so far

>550 clients	>1,300 publications
Assisted development of digital G2P services used by >875 million people	Implemented >875 DFS projects
Developed >275 FI products and channels now used by >55 million people	Trained >10,500 leading FI specialists globally

Some of our partners and clients

MSC
MicroSave Consulting



[MSC corporate brochure](#) | Contact us at info@microsave.net

Asia head office

28/35, Ground Floor, Princeton Business Park,
16 Ashok Marg, Lucknow, Uttar Pradesh 226001, India
Tel: +91-522-228-8783 | Fax: +91-522-406-3773 | Email: manoj@microsave.net

Africa head office

Landmark Plaza, 5th Floor, Argwings Kodhek Road
P.O. Box 76436, Yaya 00508, Nairobi, Kenya
Tel: +254-20-272-4801/272-4806 | Email: anup@microsave.net

MSC

MicroSave Consulting