

AI-Driven Microfinance: Transforming Financial Inclusion, Organizational Performance, and Economic Development

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ABSTRACT:

Artificial intelligence opens up the potential for linkage between inclusive financial services and workforce capability and institutional performance. This study employs an integrative literature review, as well as original quantitative analysis of publicly available data from MIX Market and Global Findex. In FY 2018, there are 753 microfinance providers in the institutional cross-section, and 212 institutions in the balanced workforce panel are followed from 2011 to 2018. A total of 171 providers report human resource policies which are analysed. A retrospective predictive benchmark is a classification of operational self-sufficiency in the next annual record based on information from financial, outreach, and workforce sources from the previous year. There are 11,529 training observations and 577 validation observations used for model development, and 528 institutions reporting in calendar year 2018 used for final testing. The area under the receiver operating characteristic curve of the random forest that includes information on the workforce is 0.858, whereas a logistic model using prior performance served as a baseline with an area under the curve of 0.818. A matched financial-and-outreach forest has a value of 0.862, and offers an explicit assessment of the workforce specification. The median operational self-sufficiency of the institutional results is 114.90%, while 78.95% and 74.27% of the social-reporting institutions document social-protection and grievance-resolution policies,

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respectively. In developing economies, global Findex aggregates rose by 27.65 percentage points in 2014-24 in digital-payment participation. Four figures and six tables link the empirical results to human resource management, labour organisation, operation, industrial relations and financial inclusion. The study provides a replicable approach to assess predictive decision support and align technological capability with people, processes and productive financial involvement.

Keywords: Artificial Intelligence; Microfinance; Financial Inclusion; Human Resource Management; Labour Management.esia

Introduction

As digital infrastructure enables financial services to reach more people, financial inclusion is an organizational and development priority. According to the Global Findex Database 2025, adults in the world had a financial account in 2024, up from 51% in 2011, representing a 79% increase. This extension provides a wider base for savings, payments, borrowing and transactions of enterprises. In that environment, microfinance institutions bridge financial products and small businesses, households, and community enterprises in the working lives. Their contribution is dependent on the availability, utility and continuity of the services that the client receives. (World Bank, 2025)

AI-driven microfinance includes the implementation of predictive models and AI support in areas like credit assessment, communication with service, and decision support for employees. Research on the use of micro-credit scoring and unserved borrowers offers evidence that analytical tools can augment the information available for lending decisions. Their value in terms of organization becomes evident when model results become part of the work routines of employees and effective service processes. This study thus investigates technology along with the management practices that enable

the capability of analysis to be used in financial-service delivery. (Ampountolas et al., 2021; Li et al., 2024)

The investigation is organized around four dimensions of management. Human resource management is related to the selection, learning, development, support in performance, and career progression of employees. Labour management issues involve issues of task allocation, workload coordination, working practices and deployment of employee time. Operations management deals with the design and management of the lending and service process, from the application to the ongoing service to the client. Industrial relations is the institutional framework that enables workers and their unions to engage in processes of decision making regarding work, skills and technological change. The strategic human resource theory and evidence related to social dialogue serves as a foundation to consider these dimensions as interrelated aspects of organizational performance. (Doellgast et al., 2025; Wright & McMahan, 1992)

The focus of the analysis is on the difference between institutional and client outcomes. An institution can increase its processing speed, productivity of its workforce or consistency of its services. Clients might be better able to access, have more robust business capacities, or have more capacity to invest. Economic

development is related to the broader impacts of productive activities, financial strength, and better livelihoods. These levels need to be linked together in a coherent research design, while maintaining the meaning of each outcome measured. This study builds on that link by using innovative analysis of public institutional and financial-inclusion data, a synthesis of existing evidence, and an explicit framework of managerial mechanisms.

1.1 Research aim and objectives

The study seeks to provide an explanation of the links between AI decision support, workforce development, work organization, industrial relations and institutional performance and inclusive financial services. The main research question is: What are the possibilities of public microfinance and financial-inclusion data to contribute to an integrated assessment of predictive capability, workforce management, operating performance and economic participation? There are five aims to guide the investigation.

1. To test predictive models of the operational self-sufficiency of microfinance institutions based on public financial, outreach and workforce data for the coming year.
2. To understand the concept of institutional staffing, caseload and workforce development as part of labour management and service capability.
3. To analyse the operating performance and the use of predictive information for coordination of microfinance services.
4. To explore reported employment policies and published social-dialogue evidence as institutional bases for employee support and participatory technological change.
5. To incorporate financial-inclusion trends, enterprise capability, productive investment and household economic outcomes.

The study's contribution is the management framework and the empirical results are reproducible. Public institutional records provide staffing, workload, operating performance and employment policy reports. The predictive element analyzes a specific AI application, while financial-inclusion data offer an up-to-date picture of financial-service uptake. The data collected, the model comparison, the presentation of results and the conclusions are determined by the objectives. (MIX, 2020; World Bank, 2025)

2. Literature Review

2.1 Organizational capabilities and strategic human resource management

The resource-based view sees sustained organizational advantage in the attributes and structure of resources of the organization. Dynamic-capability theory takes this view and looks at how institutions are able to integrate and renew competences in the face of changing environments. When applied to microfinance, these viewpoints focus on the interplay of data, employee knowledge, management procedures and service relationships. The strategic value of AI capabilities is realized when the institution is able to continuously link such resources with its purpose of operation. (Barney, 1991; Teece et al., 1997)

Strategic human resource management is the explanation of how to use the practices of HRM to assist the institutional goals. Wright and McMahan offer the theoretical basis for this linkage, and organizational research by Huselid links systems of HR practices to employee and firm performance. These contributions help to support learning, staffing, and performance support in an analysis of AI adoption. The capacity of employees to understand the information and respond to it is considered as an operational resource which can be developed by

coordinated management practice in this study. (Huselid, 1995; Wright & McMahan, 1992)

Technology is used in the context of everyday work arrangements. According to the unified theory of technology acceptance, performance expectations, effort expectations, social influence and facilitating conditions are relevant factors in technology acceptance and use. Edmondson's research relates team learning to psychological safety. These views serve as a basis for training, support that is available, and positive feedback from employees. Team learning serves as an institutional base for participation every day, and formal industrial-relations arrangements serve as another institutional base. (Edmondson, 1999; Venkatesh et al., 2003)

2.2 AI, alternative data, and inclusive credit assessment

Digital information can supplement traditional borrowers' records, as illustrated by financial-service research. Berg et al. explore the predictive value of digital footprints, and Jagtiani and Lemieux take a look at other information and machine learning in fintech lending. Björkegren and Grissen demonstrate that there is information in mobile-phone usage patterns that can be used for predicting repayment. These studies provide an information base for assessing clients whose financial records are provided by a broader range of observable activities. (Berg et al., 2020; Björkegren & Grissen, 2020; Jagtiani & Lemieux, 2019)

Research specific to microfinance builds on this analytical underpinning, and links it to the institutional dimension of lending. Ampountolas et al. compare machine-learning techniques for borrower classification based on the records of microfinance institutions in Ghana. Caire and

Fernandez Vidal show how the information from transactions is used in the credit assessment process for micro and small enterprise lending in India. For underserved borrowers, a complementary study of banking by Li et al. reveals increased approval rates and better repayment outcomes after the AI-powered scoring system. There are thus different types of evidence in the literature, related to predictive information, institutional application and actual access. (Ampountolas et al., 2021; Caire & Fernandez Vidal, 2024; Li et al., 2024)

In this study, inclusive credit assessment is viewed as an integrated credit assessment process. Data needs to be gathered; employees need to be aware of the information they need to support the decision and outcomes of their application need to be clearly communicated to the client. At each of these stages human resource and operations management are involved in the analysis. Therefore, the suggested relationship between analytical ability and inclusion relies on the practical organization of the work related to the lending decision.

2.3 Employee capability, AI assistance, and labour management

In the management literature, automation and augmentation are two approaches that are used in conjunction with AI. Raisch and Krakowski demonstrate the evolution of their relationship, over tasks and over time. Tambe et al. link AI in HRM to the process of problem definition, analytical thinking, and organizational implementation. These views can guide the design of the roles of employees, where AI support, professional judgement, and ongoing learning work together to reinforce each other. (Raisch & Krakowski, 2021; Tambe et al., 2019)

Measured evidence comes from workplace studies for this relationship. Brynjolfsson et al. examine AI support for customer support; Noy and Zhang conduct an experimental study of consultants working on knowledge-work tasks; and Dell'Acqua et al. analyse AI support for customer service. Their results show increases in productivity or performance on tasks studied. These studies provide information for analysis of communication and information preparation and employee support as potential areas for productive assistance for microfinance. The evidence is applied to a new institutional context when they are transferred to specific microfinance jobs. (Brynjolfsson et al., 2025; Dell'Acqua et al., 2026; Noy & Zhang, 2023)

2.4 Operations management and institutional performance

Research on microfinance digitization indicates that the following areas are crucial: Operations information, employee development, leadership, and workflow redesign. The institutional pathways to digitization are captured in CGAP case studies, and later in loan-automation pilots, cross-functional teams, dashboards, and iterative implementation are highlighted. This is backed up by nearby evidence of mortgage lending that relates technology-driven operations to quicker processing. These studies suggest a process perspective that institutional performance relies on the coordinated changes in information flow and work execution. (Flaming & Jeník, 2021; Flaming et al., 2023; Fuster et al., 2019)

The operations point of view brings a quantifiable contribution to the workforce of angle. The effectiveness of a credit officer can be measured by the number of cases completed, the quality of the work performed in processing the cases, and the time spent working with clients. As coordination,

coaching and resolving cases for judgment, the branch management can be analyzed. This study thus considers workforce productivity and service throughput as related outcomes in a single operating system.

2.5 Industrial relations, consultation, and technological change

Research in the field of industrial relations offers some evidence of the means by which employees are involved in technological change. The ILO case studies on social dialogue on AI and algorithmic management are recorded. Haipeter et al. analyse the involvement of employees at Deutsche Telekom, such as agreements and organisational structures for AI. In his laboratory study, Milanez will investigate structured worker consultation on algorithmic-management features. These sources create the notion of participation and negotiated learning as objects of organizational analysis. (Doellgast et al., 2025; Haipeter et al., 2024; Milanez, 2025)

More comprehensive OECD evidence of workplaces relates implementation to employee experience. The employer survey, the worker survey and the qualitative case studies focus on perceptions of performance, training and consultation, and on describing changes in tasks, skills, and work organisation in finance and manufacturing. These contributions are analyzed in this study to differentiate individual learning, team participation and formal representative dialogue. They both work at different organizational levels, and can be analysed by the related data. (Lane et al., 2023; Milanez, 2023)

2.6 Financial inclusion, enterprise capability, and economic development

Financial services and productive activity and livelihoods are linked through development

research. Dupas and Robinson find positive effects of saving access for female market vendors in Kenya on productive investment. Suri and Jack link mobile-money access with household economic advancement and women's occupational choices. These contributions set the ground for the development of relevant development outcomes for a microfinance research agenda. (Dupas & Robinson, 2013; Suri & Jack, 2016)

The ability of an enterprise is another linkage between finance and management. The experiment conducted by Karlan and Valdivia looks at training microfinance clients in business and finds that business knowledge increases and client retention improves. This evidence is used to guide the service and learning aspect of microfinance and the assessment of the client's capability and institutional staff development. (Karlan & Valdivia, 2011)

2.7 Predictive learning for operational decision support

Random forests are a combination of several decision trees, which are used to model nonlinear relationships between predictors. Their application in this study offers a tangible example of how AI can be applied to microfinance operations to predict. The question of the research is whether past institutional information can differentiate the subsequent annual records above and below the operational self-sufficiency threshold. This task is a machine learning task that relates to organizational information management. (Breiman, 2001)

2.8 Integrated analytical contribution

At the analytical model, employee, institutional and household levels, complementary evidence is offered in the literature. The aim of this study is to link those levels in four managerial mechanisms:

employee capability development, purposeful organization of labour, coordination of service operations, and involvement in technological change. The resulting framework suggests that these mechanisms can help to turn AI capability into useable financial services. The developmental endpoints are enterprise and household outcomes, which can be used to measure the broader impact of microfinance. This comprehensive interpretation will inform the categories for data extraction and the analysis that will follow.

3. Methodology

3.1 Research design and evidence integration

This study takes a mixed method approach, including an integrative literature analysis, institutional descriptive analysis, a retrospective machine-learning benchmark, and analysis of published financial-inclusion aggregates. The design links observable measures of the workforce and measures of operations to a clearly defined application of AI in the future. The literature component is based on the principles of integrative review and links evidence from the finance, management, employment relation and development fields. There are 35 works in the reference base, theoretical, empirical, methodological and public data sources. These works have different analytical functions in the study. (Snyder, 2019; Whittemore & Knafl, 2005)

The literature was purposefully chosen based on its relevance to the five objectives, the traceability of the methods used and the relationship between the reported evidence and the organizational context. The evidence base consists of peer-reviewed publications and primary reports from CGAP, the OECD, the ILO and the World Bank. Extraction records document the source, context,

research design, population, management dimension, measured outcome and appropriate interpretation. Thematic analysis groups the material together by analytical capability, workforce development, labour organisation, operations, industrial relations, financial participation, and development. Interpretation is from reported evidence to managerial mechanisms, and focuses on the level of measurement for each result. (Braun & Clarke, 2006)

3.2 Public data collection and analytical samples

MIX Market provides institution-level financial and social-performance records, company metadata and field definitions. The financial-performance workbook in USD, social-performance workbook, company metadata and both definition workbooks published via the World Bank Data Catalog are used in this study. The downloaded financial file has 41,258 annual and quarterly records for 3,116 institution identifiers. Annual records selected: 20,120 observations; one complete record kept per institution and fiscal year: 20,096 observations. The descriptive cross-section is based on fiscal year 2018, the most recent year for which there is significant annual coverage in this archive. (MIX, 2020)

Global Findex provides published aggregates of survey data on account ownership and use of payments, borrowing and savings services. This study uses the Global Findex Database 2025 workbook and chooses the published developing-economy aggregate (code LMY), and then sets both of the population-group fields to all. The four selected waves (2014, 2017, 2021, and 2024) allow observations of all four financial-participation measures. These are the weighted aggregates for adults (15 years of age and older) of the source. The

published values are used for the analysis. (World Bank, 2025)

Table 1. Public datasets and analytical cohorts

Component	Source and period	Analytical unit	Sample
Institutional profile	MIX financial data; FY2018	Institution	753 providers; 87 countries
Workforce trajectories	MIX financial data; FY2011-FY2018	Institution-year	212 institutions; 1,696 observations
Employment policies	MIX social data; FY2018	Institution	171 providers
Predictive benchmark	MIX annual pairs; target reports through 2018	Consecutive annual records for one institution	11,529 training; 577 validation; 528 test
Financial participation	Global Findex; 2014, 2017, 2021, 2024	Published developing-economy aggregate	4 indicators × 4 waves

Source: This study's sample construction using MIX (2020) and World Bank (2025). Cohorts answer different questions and are not combined into a single sample. Fiscal-year cohorts and calendar-year prediction partitions use different date definitions.

The MIX observational unit is based on the institution identifier and fiscal year. If there is more than one record for a fiscal year, the most recent record on the As of Date will retain the whole row, and the order of the original row will be used to break ties for the date. Values are not grouped over the competing rows. Country metadata are related to geographical coverage; last known legal or profit status is not used as a historical predictor. The reporting cohorts for descriptive and employment-policy analyses are separate. In 2018, each of the five employment-policy fields is analysed, but no attempt is made to use earlier questionnaire differences as employment-policy adoption histories, as all are observed across the 171 institutions selected.

3.3 Research objectives, variables, and management alignment

The measurement framework provides direct involvement of the management in data collection and analysis for the dimensions. Staffing and caseload variables refer to the deployment of labour, while workforce predictors refer to staffing intensity, role allocation and differential wages. The employment-policy variables are a description of the arrangements reported by employees. Institutional operating conditions are operating expenses and operational self-sufficiency. Findex indicators measure financial involvement on an aggregate level of the population. These measures are related to the research objectives in table 2.

Table 2. Alignment of objectives, measurements, and analysis

Objective	Measurements and evidence	Analysis	Management connection
1. Predictive capability	Prior-year financial, outreach, and workforce variables; next-year OSS	Temporal model comparison and workforce feature comparison	Information for institutional planning
2. Workforce and labour management	Personnel; borrowers per staff member and loan officer; published learning evidence	Cross-sectional summaries and balanced annual trajectories	Role allocation, workload, and employee development
3. Operations and performance	Operating-expense ratio; OSS; predictive probabilities; process studies	Institutional profile, discrimination, and probability-error analysis	Service coordination and operating sustainability
4. HR policies and industrial relations	Five reported employment policies; social-dialogue and consultation studies	Policy frequencies and thematic integration	Employee support, grievance channels, and participation
5. Inclusion and development	Account, payment, borrowing, and saving aggregates; enterprise and household studies	Four-wave trends and developmental interpretation	Financial participation and productive use of services

OSS means a state of self-sufficiency in operation. The following areas are explored using published research: employee learning, and representative participation; and through MIX policy flags: reported institutional arrangements. This study's analytical framework is the mapping.

3.4 Descriptive and longitudinal analysis

The institutional profile provides valid observation counts, medians, and 25th and 75th percentiles. The number of personnel and borrowers must be finite and nonnegative, as must be the caseload ratios.

The operating-expense ratio should be finite and nonnegative. All finite published OSS values are kept. Female borrower share is the share of female active borrowers to the total number of active borrowers, which must be positive and range between 0 and 1. Proportions are multiplied by 100 to change them into percentage measures. Each one of these variables has its own valid denominator. No imputation or percentile capping is done for descriptive statistics, and quartiles are calculated using linear interpolation.

According to MIX, OSS is financial revenue divided by financial expense, net impairment loss and operating expense. Thus, a 100% OSS indicates that the costs in that accounting ratio are covered. The operating-expense measure is the ratio of operating expense to the average gross loan portfolio. The borrowers per staff member and borrowers per loan officer indicate the number of active borrowers per staff member and loan officer, respectively. Personnel consists of people who are currently working for the institution and those who are qualified to work for the institution as a contract personnel or adviser by the source definition. (MIX, 2020)

The longitudinal workforce analysis consists of the same 212 institutions each year from 2011 to 2018. Must have positive, finite values for caseload ratios for all 8 years. Each institution is treated equally when using the annual medians. The analysis also computes the change for each institution from 2011 to 2018 and provides a summary of a distribution of these changes. This helps to maintain the separation between the difference of the cohort median and the difference of the institution medians. The frequencies of employment policies are broken down into affirmative binary reports by the 171 reporting institutions, with an

institution being able to report multiple policies.

3.5 Predictive target, variables, and temporal evaluation

The predictive task determines if the next annual OSS record will be at or above 100%. The binary target is 1 if the following annual record has $OSS \geq 1.0$, and 0 if the following annual record has $OSS < 1.0$. The reporting end dates of predictor and target records are 330–400 days apart, and both are from the same institution and fiscal year. At least 6 of the 9 candidate predictors must be observed values while the prior-year OSS and target OSS should be finite values. Each target date is preceded by its predictor date. This construction results in 12,634 eligible annual pairs during the test period 2018.

Prior-year OSS, assets, number of active borrowers, average loan balance per borrower compared to gross national income per capita, the percentage of loans in the portfolio that are in default for more than 30 days, and the percentage of borrowers who are female from the source. The three indicators of the workforce are borrowers per staff, personnel allocation ratio and average salary as a proportion of gross national income per capita. Personnel allocation is the percentage of personnel that are designated as loan officers. These measures explicitly assign an empirical role to the workforce without using the number of cases or the compensation as proxies for training quality. All inputs are before the record year.

The temporal design involves the use of target reporting dates for training, validation dates for 2017, and final testing dates for 2018. There are 11,529 annual pairs of training set from 2,159 institutions. The number of observations in the validation set is 577 from 577 institutions and the number of observations in the test set is 528 from 528

institutions. Once model selection is done, training and validation records are merged for final fitting, resulting in 12,106 development observations. This can be an evaluation of the annual performance of an on-going institutional population, with both earlier and later training records from the same institutions.

There are four specifications in the benchmark: logistic regression with only prior-year OSS; logistic regression with all 9 predictors; a random forest with 6 financial/prior-year OSS predictors; a random forest with all 9 predictors. The forest consists of 400 trees, with 70% of the available transformed features being considered for each split. Validation: Minimum leaf size: 5 to 15, Maximum leaf depth: 8 to unlimited. Selected full forest has min leaf size of 15 and no depth limit. Full logistic regression uses the inverse regularization strength of 0.1, 1 or 10, with 0.1 being selected. The strength of the previous OSS baseline is 1. The financial and outreach forest uses the selected settings from the entire forest, and makes a matched feature comparison. (Breiman, 2001; Pedregosa et al., 2011)

If a model input is not finite, it is considered missing before fitting the model. The inputs to portfolio-at-risk, female-share, and personnel-allocation are required to be in the range $[0, 1]$ while all other predictors are required to be nonnegative, except for the signed OSS accounting ratio. The training observations are used to estimate the 1st and 99th percentile caps for each fitting stage; the fitting stages apply signed log-one-plus transformations to unbounded inputs; the fitting stages perform median imputation with missingness indicators. Logistic models additionally standardize inputs. Transformations fitted on the development

data are used for the validation and test observations. The random seed is 2026. The procedures are done in Python 3.12.14, pandas 2.2.3 and scikit-learn 1.8.0. (Pedregosa et al., 2011)

3.6 Performance measures and uncertainty

The most commonly used discrimination measure is the area under the receiver operating characteristic curve (AUC). An AUC of 0.5 is considered chance ranking and an AUC of 1.0 is perfect ranking within the evaluated observations. The Brier score is the average of the squared difference between the prediction of the probability and the actual binary result, and a lower Brier score means that the probability prediction is more accurate. The balanced accuracy is the average of the sensitivity and specificity at a probability threshold of 0.5. It is included because 431 out of 528 observations in the test cohort are OSS and 97 are not. Calibration is shown in terms of 5 groups of quantiles based on the predicted probabilities.

AUC intervals are based on 1000 bootstrap samples of test institutions. The workforce feature comparison also includes the same sampled institution identifiers for both forest specifications and reports the difference between the two forests in terms of AUC. The intervals are based on resampling of the test-cohort, given the fitted models. Both values of the workforce and the missingness indicators are included in the feature comparison. A sensitivity analysis is used to eliminate pairs of annual data where there are competing institution–fiscal-year records and to re-run the chosen full-forest specification. The hyper parameter selection is restricted to the validation period and all major specifications are tested on the same 528 test institutions.

3.7 Financial-participation analysis and analytical interpretation

The four aggregate proportions are converted to percentages and changes in percentage points between 2014 and 2024 are calculated using the Findex analysis method. The indicators include account ownership, receipt of digital payments in the last year, formal borrowing and formal saving. Formal borrowing refers to the formal channels mentioned by the source, such as financial institutions, credit cards, mobile money etc.; formal saving refers to financial institutions and mobile money. The coverage and aggregate composition are kept as published. The figures refer to multiple observations of aggregates and not to a balanced panel of individual respondents. (World Bank, 2025)

The empirical components provide complementary answers. MIX captures staffing in the past, reported employment arrangements and institutional operating conditions. The machine-learning part is used to assess the predictive application of this study. Findex is a broad financial-service indicator until 2024. There is no historical AI-adoption variable available in the data and the exercise of forecasting does not recreate the availability of contemporaneous data releases. Conclusions, then, address observed institutional patterns, and the performance of predictions in the past, as well as evidence-informed management mechanisms. The findings of enterprise and household development are based on the cited studies at the unit of analysis level of enterprises and households, respectively.

Availability and replicability of data. The datasets used as sources are made public using the World Bank Data Catalog and Global Findex download portal. An accompanying analysis package includes source URLs and checksums, variable definitions, executable

scripts, sample-construction records, model results, analysis-ready observations, and publication figures. The institutional samples, numerical tables and predictive comparisons can be reproduced from identified public releases with the help of this documentation. (MIX, 2020; World Bank, 2025)

4. Results and Analysis

4.1 Institutional scale, workforce deployment, and operating performance

The cross-section for FY18 includes 753 microfinance providers in 87 countries. The median number of personnel at institutions with eligible observations is 228 and the median number of active borrowers under outreach is 21,531. The median number of borrowers per staff member is 97.5 and the median number of borrowers per loan officer is 223. These findings set a new benchmark for the interaction between staffing decisions and processes of service to clients at the organizational level. The interquartile ranges indicate that the size of the workforce and the way in which the services are delivered vary among institutions, which helps to inform management analysis that is responsive to institutional context.

Table 3. Institutional descriptive statistics, fiscal year 2018

Indicator	Valid N	Median	25th percentile	75th percentile
Personnel, persons	651	228.00	64.50	688.00
Active borrowers, persons	698	21,531.00	5,238.75	82,731.00
Borrowers per staff member	636	97.50	56.00	153.00
Borrowers per loan officer	630	223.00	154.00	359.50
Operating expenses / average loan portfolio, %	600	14.48	9.18	24.20
Operational self-sufficiency, %	618	114.90	104.58	129.79
Female share of active borrowers, %	495	54.31	41.79	87.95

Source: This study's calculations using MIX (2020). The cohort contains 753 institutions; each row uses its own valid observations.

Female share is computed from gender-disaggregated active borrower counts.

Quartiles use linear interpolation, which may produce fractional values for count variables.

The median ratio is 114.90%, and the range of the middle 50% of observed ratios is from 104.58% to 129.79%. This puts the median institution just over the accounting threshold for the predictive exercise. The median operating-expense ratio is 14.48% which represents the operating expense of the average loan portfolio based on the MIX definition. The two indicators can be analyzed together under the same operational framework and provide analysis of resource use and revenue coverage. They are not direct measures of client income or employment creation, but rather are measures at the institution level.

The median proportion of women is 54.31% of active borrowers for the 495 institutions that have gender disaggregated records. This finding is added to the staffing and performance measures to create a list of inclusive outreach measures. It also highlights the analytical importance of gender disaggregated operational information – institutions can analyse who they serve and what type of staff and operating resources are used to provide service to them. These measures in the study's management framework help to guide a coordinated review of outreach, service capacity and institutional continuity.

4.2 Workforce caseloads and labour-management configurations

The 212 institutions in Figure 1 are followed over eight fiscal years. The median borrowers per staff member in 2011 and 2018 are 121.5 and 112.5, respectively, while the median

borrowers per loan officer are 281.5 and 257.5, respectively. The staff series goes from 123.5 in 2014 to the officer series ranging from 257.5 to 289.0. The continuity between the two series is due to the different personnel denominators. The all-staff measure is a broader measure, the officer measure focuses on the lending role.

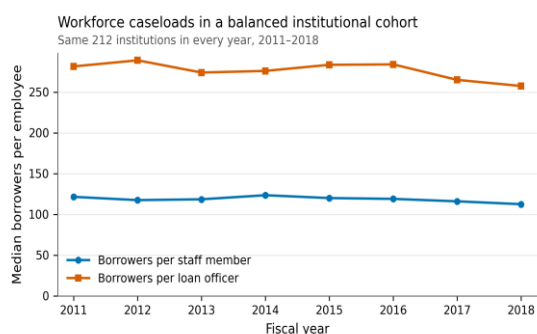


Figure 1. Workforce caseloads in a balanced institutional cohort, 2011–2018.

Table 4. Workforce caseload endpoints and within-institution changes

Caseload measure	2011 median	2018 median	Median paired change	Paired-change IQR
Borrowers per staff member	121.5	112.5	-1.5	-34.0 to 22.0
Borrowers per loan officer	281.5	257.5	-7.5	-76.5 to 61.0

Source: This study's calculations using MIX (2020); N = 212 institutions. Paired change equals each institution's FY2018 value minus its FY2011 value. IQR denotes the 25th–75th percentile interval of those changes. A median paired change is distinct from the difference between endpoint medians.

The median change in borrowers per staff member and borrowers per loan officer is a decrease of -1.5 and -7.5, respectively. The interquartile ranges for these are -34.0 to 22.0 and -76.5 to 61.0 respectively. Caseload increases in 97 of the institutions, stays the same in six, and decreases in 109; caseload increases in 99 of the loan offices, stays the same in 1, and decreases in 112. The balanced

cohort thus exhibits a distribution of staffing configurations, instead of a single sector-wide trajectory.

The role of labour-management contribution is to make the identification of caseload as an explicit planning variable. The higher ratio is the more borrowers per member in the relevant personnel group and depends on service intensity, product complexity, branch structure and work done. The outcomes serve as a starting point to evaluate staff time spent on processing, relationship management and client support. The association with AI is an implementation suggestion: institutions may consider measuring the changes in the completion of tasks and the capacity of services when employing analytical assistance and tracking the measures of caseload observed here. The interpretation of how such changes can be supported is provided in employee-development and work-organization studies. (Milanez, 2023; Raisch & Krakowski, 2021)

4.3 Human resource policies and the industrial-relations foundation

The social-performance cohort offers a firsthand look at the formal employment situation. Of the 171 providers that reported in fiscal year 2018, 135 providers reported on social-protection provisions, which accounted for 78.95% of the providers. Of the 127 institutions that report having a grievance-resolution policy, 120 (70.18%) have anti-harassment policies, 117 (68.42%) have safety policies, and 113 (66.08%) have non-discrimination policies. These frequencies are shown in figure 2. Under the source field definition social protection is medical insurance and/or pension contributions.

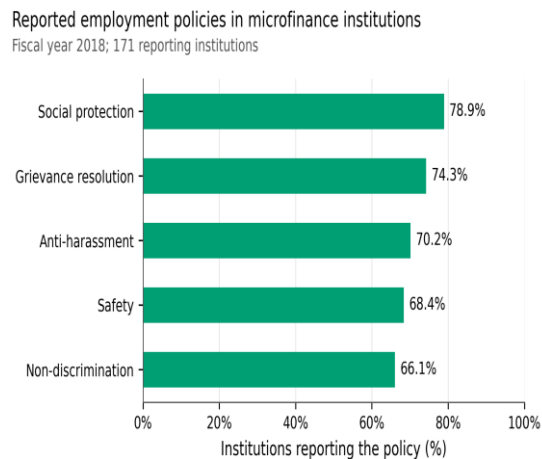


Figure 2. Reported employment policies in microfinance institutions, fiscal year 2018.

These findings put human resource management in an empirical contribution with a measurable place in the paper. Social protection is about institutional support for personnel and conduct and safety policies are about the workplace. There is a documented process for resolving employment issues (grievance-resolution arrangements). Analysis is based on the presence of reported policies. The policy variables are not indicators of implementation quality, employee experience or collective-bargaining coverage, and these are separate organizational entities.

These policy observations and published evidence about representative participation combine to develop the interpretation of the industrial-relations dimension. ILO case studies record negotiated arrangements relating to technological change and skills. Doellgast et al. mention a Brazilian banking agreement that has provisions for retraining and career development, as well as a pledge of 3,000 information-technology scholarships for women. At Deutsche Telekom, Haipeter et al. report on employee engagement via an AI manifesto, a digital roadmap and company agreements. These cases describe specific scenarios in which workforce development

and technology implementation can get into a formal dialogue. (Doellgast et al., 2025; Haipeter et al., 2024)

The pilot experiment conducted by Milanez provides new evidence of consultation as a decision process. The study comprises of 16 participants from three manufacturing companies from Germany. After formal negotiations, the companies agree to eight, seven and five out of eight algorithmic-management design elements, respectively. The agreements observed relate to simulated design decisions. In the context of microfinance, the findings of this study are understood as a foundation for engagement of employees and their representatives in decisions regarding task allocation, training and application of decision support tools. The MIX grievance and policy indicators refer to institutional arrangements adjacent to the MIX, and the participation studies mentioned name the representative channel. (Milanez, 2025)

4.4 Predictive analysis of subsequent operational self-sufficiency

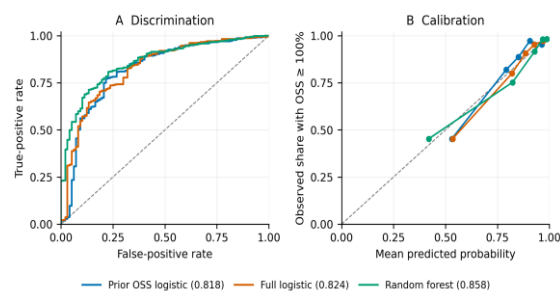
The number of institutions in the temporal test is 528, of which 431 institutions have an annual record that exceeds the OSS threshold. The random forest with workforce information has an AUC of 0.858, and a 95% bootstrap interval of 0.821–0.895. It has a Brier score of 0.110 and balanced accuracy of 0.675. These results illustrate that the information from the previous year in institutions can be used to make useful discrimination of the subsequent OSS status of the cohort of interest. Prior-OSS logistic baseline has an AUC of 0.818, Brier score of 0.121 and balanced accuracy of 0.593.

Table 5. Temporal test performance for next-year operational self-sufficiency

Model	AUC	95% AUC interval	Brier score	Balanced accuracy
Prior OSS logistic; 1 predictor	0.818	0.769–0.865	0.121	0.593
Full logistic; 9 predictors	0.824	0.778–0.870	0.119	0.605
Financial/outreach forest; 6 predictors	0.862	0.825–0.898	0.109	0.682
Forest with workforce; 9 predictors	0.858	0.821–0.895	0.110	0.675

Source: This study's modelling of MIX (2020); 528 test institutions with target reporting dates in 2018. The outcome is next-annual-record OSS $\geq 100\%$. Intervals use 1,000 test-institution bootstrap samples conditional on fitted models. Balanced accuracy uses a probability threshold of 0.5. Higher AUC and balanced accuracy and lower Brier scores indicate better predictive performance. Predictor counts exclude generated missingness indicators.

The best AUC obtained in the comparison is for the financial and outreach forest with 0.862, and a Brier score of 0.109. The overall logistic specification had an AUC of 0.824 and a Brier score of 0.119. The two forests are observed to have a higher discrimination than the two logistic specifications. The results corroborate the value of the nonlinear predictive relationships for this classification task of institutions. This is a model comparison within the study, with the same time-based test set, maintaining a direct link between the reported performance and the operation target.

**Figure 3. Discrimination and calibration of the primary predictive specifications.**

Source: This study's modelling of MIX (2020). Panel A presents receiver operating characteristic curves for prior-OSS logistic regression, full logistic regression, and the forest with workforce information. Panel B uses five predicted-probability quantile groups. Dashed lines mark chance ranking and perfect calibration, respectively. The complete four-model comparison, including the financial/outreach forest, appears in Table 5.

The difference in AUC between the forest with workforce information and the financial/outreach forest is -0.0046 with a 95% bootstrap interval of -0.0127 to 0.0041 . The workforce specification has good discrimination and the feature comparison does not show an incremental AUC gain for the three workforce features. This outcome provides a substantive analytical test for the HR angle – staffing intensity, role allocation and relative compensation are included and analysed explicitly. They are also relevant to management as a result of the outcomes of the workforce and employment policy, and not because of the supposed improvement in prediction.

When the duplicate-record sensitivity analysis is used, 525 test institutions are retained and an AUC of 0.860 and Brier score of 0.110 are generated for the full-forest. The close number match to the main results suggests that the whole row deduplication rule is not impacting the main predictive finding. Probability estimation differs from ranking in that the calibration display and the Brier scores further differentiate them. A high AUC is useful for ordered institutional outcome assessment and for determining specific probability cutoffs, an operational purpose and a consideration of the consequences of each decision.

In the context of operations management, the predictive outcome provides an assessable means of decision support. The model can be used as a research tool to help pinpoint institutions that should be given more planning attention because of their subsequent operating condition in the following year. Any institutional application would link such information with the managerial review of service processes, staffing and clients' needs. The current evidence is for retrospective forecasting and includes workforce information in the model specification. It is not a measure of actual performance of an institution after implementing an AI system.

4.5 Financial-inclusion trends and the wider development setting

The aggregates for the developing economies published here indicate that financial involvement has widened from 2014 to 2024. There is a 20.71 percentage point gain in account ownership from 54.74% to 75.45%. The most significant endpoint growth is in digital-payment participation, which grew from 34.42% to 62.08% (+27.65%). The proportion of people who borrow formally rises from 15.39% to 24.02%, and the proportion of people who save formally rises from 22.14% to 39.66%. Table 6 is the table that preserves each wave and Figure 4 shows different trajectories.

Table 6. Financial participation in developing economies, 2014–2024

Indicator	2014, %	2017, %	2021, %	2024, %	Change, pp
Account ownership	54.74	63.97	69.00	75.45	20.71
Digital payments	34.42	44.48	54.82	62.08	27.65
Formal borrowing	15.39	15.49	21.75	24.02	8.63
Formal saving	22.14	20.86	23.73	39.66	17.51

Source: This study's calculations from World Bank (2025), Global Findex Database 2025 workbook. Published developing-economy aggregate: code LMY, group all, group2 all; adults aged 15 and older. pp denotes percentage points; change equals 2024 minus 2014 using unrounded source values. The source's weighted aggregates are used directly.

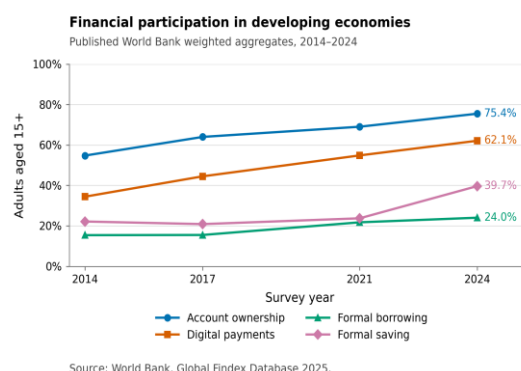


Figure 4. Financial participation in published developing-economy aggregates.

Source: This study's calculations from World Bank (2025). Points represent the published weighted aggregates for 2014, 2017, 2021, and 2024. Values are percentages of adults aged 15 and older. Wave coverage and aggregate composition are those of the source.

The four measures capture various aspects of inclusion. Ownership of an account is a fundamental link to formal financial infrastructure, while the use of financial payments for transactions is a link to the financial system that is distinct from account ownership. Savings and borrowing are links to the financial system that are separate from account ownership and payments use. The account-ownership aggregate is 13.37 percentage points higher than the digital-payment participation in 2024. This is an arithmetic difference in terms of the level of indicators and not the identification of the

account holders who are using a specific service. The pattern still has the focus of an operational service, in terms of access to accounts and use of services.

The developmental interpretation relates these trends to evidence on productive use. Dupas and Robinson's field experiment finds that female market vendors that were given access to savings increased their saving and productive investments. Training their microfinance clients leads to improvements in business knowledge and institutional client retention, Karlan and Valdivia find. Suri and Jack estimate that mobile-money expansion in Kenya lifted around 194,000 households out of poverty and helped to shift women's occupational preferences. These results provide relevant enterprise and household outcomes in their contexts. The Findex trends offer a wider participation context; the referenced studies offer insights into specific ways in which financial services can contribute to economic progress. (Dupas & Robinson, 2013; Karlan & Valdivia, 2011; Suri & Jack, 2016)

4.6 Integrated analysis of AI, people, processes, and inclusion

The overall results justify an interpretation of the data within an integrated organization. The predictive benchmark is a measure of analytical ability. The institutional profile and balanced panel are direct evidence of workforce deployment and operating conditions. The employment-policy frequencies reflect formal HR arrangements and the industrial-relations literature shows the ways in which involvement in technological change can be facilitated. The financial participation is a population-level setting added by Findex. The individual components thus provide a distinctive observable aspect of the research context.

Published microfinance evidence can help to link the pieces together. In a combined digitization programme, CGAP's Bancamía case reported a 27% rise in officer productivity, and a 52% decrease in processing time. The Flaming et al. broader pilot programme highlights cross-functional teams, operational dashboards and iterative loan-process development. These results relate workforce and operational redesign to outcomes that can be measured. The present MIX analysis provides the staffing and operating conditions under which related institutional questions can be analyzed and the implementation context of the original case studies is retained. (Flaming & Jeník, 2021; Flaming et al., 2023)

The role of information is explained in the credit-assessment literature. When they add repayment and transaction data, they get an AUC of 0.82, versus 0.69 with repayment history alone, according to Caire and Fernandez Vidal's Fundfina analysis. Ampountolas et al. review the use of machine learning in micro-credit scoring, while Li et al. look at AI-based credit scoring of underserved borrowers. This study's model focuses on subsequent institutional OSS, while these studies focus on borrower assessment and access. The analytical contribution is shared, disciplined analysis of predictive information in comparison to a specified outcome, followed by a management application based on the decision being supported. (Ampountolas et al., 2021; Caire & Fernandez Vidal, 2024; Li et al., 2024)

With employee capability, decision support has an organization channel. Brynjolfsson et al. found a 15% productivity boost in their study of 5,172 customer-support agents who were assisted by AI. In a professional-writing experiment, Noy and Zhang claim a 40% time

saving and an 18% improvement in output quality as measured by their experiment. Results of these findings help to pinpoint where task performance can be improved with the help of these activities. Their relevance for microfinance is related to the design of communication, information preparation and learning support. Training priorities would be based on the work of the actual loan officers, service personnel and branch managers. The MIX results can be used as workload measures for future evaluations of the roles. (Brynjolfsson et al., 2025; Noy & Zhang, 2023)

The coordinated measurement approach is the management contribution of this study. HR management can help with workforce development and employee support, labour management can help with role and workload allocation, operations management can help with process and performance and industrial relations can help with consultation and representative participation. The two perspectives of the resource and dynamic capability are the reasons for the consideration of these organizational elements together. The joint causal contribution is a proposition for institution-level implementation research, and the present paper provides public-data measurements, a clear predictive comparison, and source-grounded mechanisms that enable the proposition to be empirically actionable. (Barney, 1991; Teece et al., 1997; Wright & McMahan, 1992)

5. Key Findings and Managerial Implications

5.1 Predictive capability can be assessed against an operational outcome

The first goal is accomplished by conducting a temporal test of 528 institutions. The forest with workforce information has an AUC of 0.858, whereas the previous OSS baseline

forest has an AUC of 0.818, and the matched forest with financial/outreach information has an AUC of 0.862. The paired workforce comparison is a comparison of the contribution of the selected variables and the contribution of the second variable is not interpreted as an incremental AUC gain. The managerial take is to assess the contribution of AI decision support in relation to an institutional outcome and appropriate comparators before drawing conclusions about its contribution to the organization.

5.2 Workforce management has a direct quantitative foundation

Staffing summaries and a balanced panel of 212 institutions are used to address the second objective. The median changes in borrowers per staff and loan officer per staff for each institution in the cohort reveal the variation in workload allocation among institutions over time. The discovery backs up a role-specific strategy to labour administration that involves a mix of caseload, task substance, service level and employee development. The complementary learning and process context are provided by published workplace and microfinance evidence.

5.3 Operating performance and service capacity can be reviewed together

The third objective is related to workforce deployment, resulting in median OSS of 114.90% and median operating-expense ratio of 14.48% in the reporting cross-section for FY2018. The forecast exercise is an analytical exercise that is forward-looking and is added to those descriptive measures. The resulting framework enables operational planning to link the revenue coverage, use of resources, and deployment of personnel, and to keep service quality and client outcomes separate.

5.4 Employment arrangements provide a measurable HR foundation

The five policy indicators and the industrial-relations synthesis are reported indicators of the fourth objective. The 171 social-reporting institutions report on social protection (78.95%) and grievance resolution (74.27%). These observations record formal arrangements for employees' support. There is also published evidence of consultation and collective-agreement that can be used as a basis for engaging employees and their representatives in the design of training, work organization and technological change.

5.5 Financial participation supplies the development context

The fourth objective is covered in four waves of Findex and in the enterprise-development literature. The published aggregates of the developing economies rise by 20.71 percentage points in account ownership, 27.65 in digital payments, 8.63 in formal borrowing and 17.51 in formal saving between 2014 and 2024. The findings are consistent with the need to focus on the productive utilization of financial services. The development literature relates specific financial and learning interventions to investment, business knowledge, retention and household advancement in the settings studied.

6. Conclusion

This study is a pioneering study in the field of microfinance research using AI tools, combining original public data analysis with a significant human resource, labour-management, operations, and industrial-relations focus. The empirical design connects 753 reporting institutions in the FY2018 cross-section, a balanced workforce panel of 212 institutions, 171 social-performance reporters, a temporal predictive

test of 528 institutions and four waves of published financial-inclusion aggregates. The objectives, measurement options, results and conclusions are structured around the same management and development questions.

The predictive contribution is tangible: a random forest model with financial, outreach and workforce information discriminate next-annual-record OSS status with an AUC of 0.858. The financial/outreach forest has an AUC of 0.862 and the paired comparison design sets the observed performance of the workforce specification and does not assume an incremental gain. The institutional results include median OSS of 114.90%, differentiated workforce caseloads, and documented employment-policy arrangements. These combined results bring institutional performance and workforce management into the realm of what is observed.

The overall inclusion analysis reveals significant growth in account holdings, formal payments, formal borrowing, and formal saving, from 2014 to 2024. Specific studies of enterprises and households published are helping to understand the role that specific financial services and learning interventions can play in supporting productive activity. The developmental argument that emerges is one that links analytical skills with the individuals and the processes that enable institutions to provide services and links participation in services with clearly defined enterprise and household outcomes.

The study finds that there are four key areas of coordinated evidence that can be used to assess AI-enabled microfinance: predictive performance, workforce deployment, employee support, and operating conditions, as well as financial participation. Human resource management brings learning and

institutional support; labour management brings organization of work; operations management brings the linkage between resources and service processes; and industrial relations brings in the linkage for participation in technological change. The

paper's public data analysis is reproducible, and provides a foundation for institution-specific evaluation of these relationships, as well as for the development of productive, inclusive, and organizationally sustainable financial services.

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