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Technical Efficiency of Microfinance Institutions in Nepal: A Stochastic Frontier Approach

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Abstract
This study examines the technical efficiency of microfinance institutions in Nepal. It provides valuable empirical evidence on Nepalese microfinance institutions' wasted resources and inefficiency. The gross loan portfolio is the output variable, while total assets, cost per borrower, and human resources are input variables. A total of 168 observations from the panel data of 24 microfinance institutions covering the period from 2016/17 AD to 2022/23 AD were analyzed for this study. Data and other necessary information were collected from the audited annual reports of microfinance institutions and the Nepal Rastra Bank. Technical efficiency was calculated using a stochastic frontier model with a production function as the efficiency measure. This study found that total assets, human resources, and cost per borrower significantly influence loans and advances in Nepal's microfinance institutions. The average technical efficiency of Nepalese microfinance institutions is 77.76 percent. It was also found that microfinance institutions operating for more than 10 years are more efficient than those operating for less than 10 years. Province-level MFIs exhibit the highest technical efficiency compared to national- and district-level MFIs. The findings have significant implications for policymakers of microfinance institutions to utilize their resources better and improve efficiency. This study serves as a valuable foundation for increasing the number of micro-entrepreneurs by minimizing the wasted resources of Nepalese microfinance institutions. The technical efficiency estimates reflect the resource mobilization level of these institutions. This study is distinct from previous research as it is the first to utilize recent panel data of Nepalese microfinance institutions along with the application of the stochastic frontier model.

Keywords*:* Technical efficiency, panel data, stochastic frontier model, microfinance institutions

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Introduction

Microfinance institutions (MFIs) offer banking services to individuals and groups with low incomes who generally lack access to traditional financial services. The nature and scope of the activities of microfinance institutions (MFIs) differ significantly from those of traditional financial and banking organizations. Due to their limited capital, they often operate locally, providing security-free group loans to small farmers, low-income households, and other marginalized groups. Under the condition of credit for service opportunities, microfinance institutions provide small business loans to their lower-income clients, typically communities, to reduce poverty and promote economic development (Bruton et al., 2011). Those genuinely in need but do not have access to traditional banking sector institutions provide nonfinancial and financial services without the need for collateral (Khavul, 2010). The defining features of microfinance are small loans, group lending, savings groups, small-scale entrepreneurs, varied utilization, prompt payback, careful supervision, and straightforward credit terms and conditions, that is, without collateral (Nepal Rastra Bank, 2013).

The primary goal of MFIs is to provide their clients with financial and non-financial services that support their efforts to eradicate poverty, empower women and other marginalized groups, create jobs, facilitate the socioeconomic transformation of society through self-employment, and motivate and inspire small business owners by extending credit to them without the need for physical collateral (Dhungana, 2018; Regmi, 2013).

Microfinance originated at the start of the Grameen Bank project in Bangladesh in 1974. In 1976, Muhammad Yunus, a professor at the University of Chittagong in Bangladesh and the 2006 Nobel Peace Prize winner, founded the Grameen Bank, also known as the Rural Bank (Kasali et al., 2015).

In the Nepalese context, microfinance institutions, designated as ‘ D’ classified banks and authorized by the Nepal Rastra Bank (NRB), the central bank of Nepal, are instrumental in meeting the monetary requirements of people and small enterprises that lack access to conventional banking services. These entities are crucial in providing microcredit and various financial facilities to underprivileged individuals with limited or no capital.

In underdeveloped countries, microfinance is vital for achieving sustainable development. The initial goal of microfinance institutions (MFIs) was to reduce poverty for social purposes. However, within the past 20 years, MFI operations have shifted from being socially oriented to commercialized (Rauf & Mahamood, 2009; Sriram, 2010). The primary goal of MFI is to offer banking services to those who are financially excluded, focusing on giving borrowers small loans (Mersland & Strom, 2009). Thus, to maintain their services, MFIs need to be sustainable. MFIs demand exorbitant interest rates, even greater than commercial banks, to achieve sustainability (Ahmed, 2002; Diop et al., 2007; Obaidullah, 2008). According to Hartarska (2005) and Tulchin (2003), MFIs face challenges because of their dual goals of sustainability and outreach. MFIs began to transition into commercial organizations as they worked toward self-sufficiency.

In this competitive age, efficiency is key to long-term growth and sustainability. Microfinance institutions prioritize lending to legitimately impoverished individuals in need while building a viable company independently. The financial sustainability of MFIs by earning enough revenue to cover their operating and financial expenses can be achieved through the effective resource management of MFIs (Singh et al., 2013).

Technical efficiency is the ability and willingness of any firm to maximize its output with a given set of inputs. The foundation for MFIs' long-term survival and effective operation for patients with MFIs is paramount. It speaks to institutions' potential to make enough money to cover, at the very least, the opportunity cost of all inputs and assets (Chaves & Gonzalez, 1996).

Microfinance is instrumental in promoting entrepreneurship and combating exclusion in developing nations (Dupas & Robinson, 2013; Khandker, 2001; Pitt & Khandker, 1996). In particular, microfinance's twin social and commercial missions set it apart from traditional banking and put ongoing pressure on microfinance institutions (MFIs) that genuinely pursue both goals.

The efficiency of microfinance is a critical concern, and MFI management strategies have prioritized cost containment and efficiency (Blanco-Oliver et al., 2016). Efficiency analysis is becoming increasingly important in this industry as capital market funding increases. Furthermore, a better understanding of efficiency's role in balancing microfinance's financial and social goals helps explain why microfinance is so efficient (Bassem, 2008). This study aims to measure the efficiency of Nepalese microfinance institutions at the individual level, age, and branch of MFIs. After this introduction, a literature review focusing on the historical development of microfinance in Nepal, technical efficiency, related concepts, and empirical studies is presented in the literature section. The methodology section includes research design, data, and methods. The analysis and interpretation of the data are presented in the Results section, followed by a discussion and conclusion in the final section.

Literature Review

Historical Development of Microfinance in Nepal

The first 13 credit cooperatives were founded in the Rapti Valley of the Chitwan region in 1956, thanks to a government executive order and assistance from USAID/Nepal. This marked the beginning of efforts to develop microfinance services in Nepal. These cooperatives aimed to give the Valley's flood-affected residents credit. Previously, only unofficial sources could meet the rural sector's credit requirements.

Nepal has almost 67 years of experience in microfinance. Despite several programs launched to alleviate poverty, only microfinance programs are considered pro-poor and rural-centered. The Nepal Rastra Bank has established various microfinance development programs, such as the deprived sector credit program and other donor-supported microcredit programs (NRB, 2013).

In Nepal, challenging topography, isolation, diverse populations, and cultures, among other factors, have made it challenging to provide microfinance. To advance the interests of the underprivileged by offering banking and financial services and helping to raise their economic and social standards, microfinance institutions are specialized institutions that pursue income-generating operations. The locally sustainable microfinance model has a meaningful impact on the aforementioned regions in Nepal to improve the socioeconomic status of low-income households and increase employment opportunities by encouraging the participation of small and medium enterprises (NRB, 2013).

Technical Efficiency and Approaches to Measuring It

Technical efficiency was described by Farrell (1957) as a producer's capacity to generate the most significant amount of output, given a set of inputs. A producer's technical efficiency is based on comparing observed and ideal values of inputs and outputs (Fried et al., 2008). Technical efficiency increases when a producer can utilize the same inputs to generate more of an output (oriented focused) or when a producer can generate the same outputs with fewer inputs (input-oriented) (Koopmans, 1951). Technical efficiency was characterized by Balkenhol (2007) as the best possible mix of staff time, resources, and subsidies (inputs) to achieve financial self-sufficiency, outreach to people with low incomes, and generate the most significant number of loans (outputs).

Data Envelop Analysis (DEA), a non-parametric approach, is a linear programming method that makes it possible to determine a business unit's relative efficiency (Charnes et al., 1978). The Malmquist index, which breaks down productivity changes into efficiency and technology changes, can be computed using DEA. One way to view the indicator is as a total factor productivity index. It considers whether businesses use resources more effectively to create goods and services, and whether technological advancements have positively or negatively affected society. Basic DEA models use two approaches: output-oriented and input-oriented. While the output of an output-oriented model is proportionately maximized while the inputs are held constant, input reduction is proportionally maximized in an input-oriented model.

Stochastic frontier analysis (SFA), an econometric technique developed by Aigner et al. (1977) and Meeusen & Van den Broeck (1977), can be used to gauge efficiency. SFA breaks down the error term into two parts—one to account for random effects and the other to account for technical inefficiency—and outlines the link between output and input levels. SFA is a parametric technique that specifies a functional form for the production, profit, or cost function and provides a composed error model in which random error is assumed to follow a symmetric distribution and inefficiencies an asymmetric one (Greene, 2005b).

Technical Efficiency for Microfinance Institutions

Efficiency in microfinance institutions is the effective use of resources, including assets, human capital, and subsidies, to generate output, expressed in the number of active borrowers and loan portfolios. Measuring efficiency in MFIs is also highly important because it provides information on a company's success, particularly concerning resource usage and waste reduction (Reynolds & Thompson, 2002). Bassem (2008) stated that efficiency in microfinance organizations is the degree to which they successfully distribute personnel, assets, and subsidies to generate output assessed in terms of the loan portfolio and poverty outreach. Either the production approach, which examines an MFI as a production unit using inputs to produce outputs, or the intermediation approach, which examines an MFI as a financial intermediation unit involved in directing credit from areas of surplus to areas of deficit, is used to analyze microfinance institutions (Fried et al., 2008).

Microfinance institutions use capital, employees, and assets as input resources to produce loans and deposits (Bassem, 2008; Haq et al., 2010). The production approach evaluates the effectiveness with which microfinance organizations employ input resources to produce output (Gutiérrez-Nieto et al., 2009). In contrast, the intermediation method views microfinance organizations as a financial intermediary that sources deposits and borrowings from surplus units and distributes them to low-income clients with deficits. While the intermediation approach is more suited for financial institutions because of its ability to gauge how efficiently deposits and loans are mediated between lenders and borrowers, its use in microfinance institutions is limited (Ahmad, 2011; Bassem, 2008).

Methodological Framework of Technical Efficiency

Technical efficiency can be divided into output- and input-oriented (Masood & Ahmad, 2010). Input-oriented technical efficiency describes a firm's capacity to reduce its inputs relative to a specific output level. The company's ability to maximize output from a given quantity of inputs is demonstrated by output-oriented technical efficiency.

A firm's technical efficiency is determined by its distance from its production frontier. Technical efficiency is an attribute of a company operating on the production frontier. The idea of a production border originally appeared in the well-known work of Farrell (1957), who established the phrase "production frontier" and provided a metric of productive efficiency. This study's stochastic frontier approach (SFA) provides at least two advantages. First, the underlying premise of nonparametric techniques is that inefficiencies cause all variances in business performance. This assumption is flawed because it fails to account for external shocks, missing variables, and measurement errors. Second, hypotheses can be tested for the parameters that the SFA estimates. The primary drawback of parametric approaches is that they force a functional form on the data, making the efficiency assessment contingent on the accuracy of the functional form as a representation of the underlying model.

The specification produced by Battese and Coelli (1995) for panel data can be expressed as:

$Yit = \exp(xit\,\beta + Vit - Uit)$…………(1)

xit is a vector of (1×K) input variables of the i-th microfinance institution at time t. β is a vector of the unknown parameters (1×K) to be estimated.

Vit is assumed to be an independent and identically distributed random error with a normal distribution with mean zero and unknown variance σv2. Uit and Vit are non-negative random variables associated with the technical inefficiency of production, which are assumed to be independently distributed. Uit is obtained by truncation (at zero) of the normal distribution with mean μ and variance σ2.

Where μit is defined as $\mu it = zit\,\delta + Wit$ .... (2)

zit is an (m × 1) vector of variables associated with technical inefficiencies in firms' production. δ is an (m × 1) vector of unknown parameters to be estimated. Wit are unobservable random variables, which are assumed to be independently distributed, obtained by truncating the normal distribution with mean zero and unknown variance σ, such that Uit is non-negative ($Wit \geq - zit\,\delta$).

Battese and Corra (1977) mentioned specification for variance parameters

$\sigma s2 = \sigma v2 + \sigma 2$

$\gamma = \sigma 2 / \sigma s2$

The value of γ ranges between 0 and 1. The zero value of γ indicates that the variance of the inefficiency effects is zero, and deviations from the frontier are entirely due to noise. A value of γ = 1 indicates that all deviations are due to technical inefficiencies.

The technical efficiency of the i-th firm at the t-th period is given by

$TEit = \exp(-Uit) = \exp(- zit\,\delta - Wit)$

Hypothesis tests were carried out to determine the importance of the parameters by imposing restrictions on the model. Utilizing generalized likelihood ratio statistics (λ), we can ascertain the importance of the constraints placed on the model.

The generalized likelihood ratio statistics are defined by $\lambda = - 2 \ln [L (H0) / L (H1)]$, where L (H0) and L (H1) are the values of the likelihood function under the null and alternative hypotheses H0 and H1, respectively. The distribution of λ is roughly chi-square with degrees of freedom equivalent to the total number of constraints. λ has a mixed chi-square distribution with the number of degrees of freedom equal to the number of restrictions imposed under the null hypothesis γ =0, which indicates that technical inefficiencies are not present in the model, and γ = δi = 0, which indicates that inefficiency effects are not stochastic (Coelli, 1995).

Efficiency of Microfinance Institutions in Global Context

Masood and Ahmad (2010) used the stochastic frontier approach to assess technical efficiency and the factors influencing it for 40 microfinance institutions that operated in India between 2005 and 2008. The study found that technical efficiency started to decrease but increased over time. They also demonstrated that although MFI size became irrelevant, MFI age was a positive and substantial predictor of efficiency.

Ahmad (2011) conducted a study to estimate the efficiency of MFIs in Pakistan using non-parametric Data Envelopment analysis, taking data for the years 2003 (12 MFIs) and 2009 (19 MFIs). Taking the gross loan portfolio and number of active borrowers as output variables, and total assets and number of personnel as inputs, he found a decline in efficiency for most MFIs in 2009 compared to 2003. By applying the stochastic frontier model to MFIs in Ghana from 2007 to 2010, Oteng-Abayie et al. (2011) discovered a mean technical efficiency of 56.29%. The study also shows that cost per borrower, productivity, and outreach are important factors that determine the effectiveness of MFIs in Ghana.

Kipesha (2012) used a non-parametric technique (data envelope analysis) to assess the effectiveness of microfinance organizations operating in East Africa. This study used a production strategy to assess the efficiency scores of 35 MFIs under both constant and changing returns to scale. The findings indicate that, on average, MFIs in East Africa have higher efficiency scores. The average technical efficiency scores for the three years under review were 0.823, 0.892, and 0.891 under variable returns to scale and 0.706 (2009), 0.798 (2010), and 0.852 under constant returns to scale. Despite the low efficiency scores in 2009 and high efficiency scores in 2011, the average efficiency trend was positive. Using stochastic frontier analysis, Zerai and Rani (2012) examine the technical efficiency of Ethiopian microfinance institutions (MFIs) from 2004 to 2009. They found that the mean technical efficiency was 71.72 percent, indicating significant room for improvement without additional resources. The study also determined that the overall assets of MFIs, the sustainability of their operations, and the proportion of female employees were important factors influencing their technical efficiency.

Annim (2012) assessed efficiency using both parametric (Stochastic Frontier Analysis, SFA) and non-parametric (DEA) methodologies, drawing on data from the World Bank and MIX Market to create a balanced panel dataset of 164 MFIs across five regions of the world between 2004 and 2008. Gross portfolio, financial income, and the proportion of female borrowers were considered as dependent variables, while operating costs, personnel, cost per staff member, and cost per loan served as input variables. According to the data, the average pure technical efficiency for narrow sustainability increased from 42.7% in 2004 to 54.3% in 2008. The total loan portfolio and cost per borrower were strongly correlated with inefficiency.

Kipesha (2013) examined the technical efficacy of microfinance institutions functioning in Tanzania. For this study, 29 MFIs were chosen, and pertinent data were gathered between 2009 and 2012 from secondary sources. The Data Envelop Analysis model was used to assess the data. He disclosed that when production efficiency was considered, a higher average technical efficiency was noted, and scale errors caused the majority of MFI inefficiencies. Additionally, he discovered that the average technical efficiency scores for the three years were 0.05, 0.1321, and 0.2531 under intermediation efficiency, and 0.7796, 07731, and 0.8586, respectively. Singh et al. (2013) employed input and output-oriented nonparametric DEA techniques to assess the efficiency of 41 MFIs in India. Tobit regression was later employed to determine the factors that influence efficiency. The study's conclusions showed that MFIs' output could be boosted by 59.4%: 25 MFIs underwent economies of scale under an input-oriented strategy, 10 MFIs under an output-oriented approach, and MFIs located in southern India were shown to be more efficient. Using data from 2006 to 2010, Olasupo and Afolami (2013) examine the technical efficacy of Nigerian microfinance banks (MFBs). They showed that, during the study, the MFBs' average client base increased by 10.57 to 21.99%, indicating a boost in outreach. They discovered that the MFB's mean annual technical efficiency score under the input-oriented metric was 0.4643, greater than the mean annual efficiency score under the output-oriented metric (0.4112).

In 2015, Riaz and Gopal used stochastic frontier analysis (SFA) to investigate the inefficiencies of microfinance in Pakistan. They discovered that MFIs have a poor average efficiency, with a technical efficiency score of only 87%. Inefficiency is negatively correlated with age and customer count, although the relationship between other variables and the operational status of MFIs is dependent on the former.

Using a Cobb-Douglas stochastic frontier model, Oteng-Abayie et al. (2016) investigated the technical effectiveness of 66 Credit Unions (CUs) in Ghana from 2009 to 2012. Using production and intermediation methodologies for efficiency modelling, they discovered that for the production and intermediation models, the average technical efficiency over the period for the sampled CUs was 53.40% and 57.96%, respectively. Additionally, they discovered that productivity and the number of employees are important factors that affect the technical effectiveness of CUs. According to Abdulai and Tewari (2016), who conducted an efficient microfinance institution study in sub-Saharan Africa using a stochastic frontier approach, MFIs now achieve a mean cost efficiency of 40.09 percent, indicating that they are not cost-effective in their intermediation role. Additionally, they illustrated how the primary factors determining an MFI's efficiency are its total assets, ratio of operating expenses to assets, average loan balance per saver, percentage of female borrowers, and the number of borrowers per employee. Using stochastic frontier analysis, Gebremichael and Gassesse (2016) investigated the technical effectiveness of 134 MFIs across 36 African nations. Their findings revealed that, on average, their technical efficiency score was close to 0.49, meaning that, given the same inputs, their outputs might have doubled. Additionally, they discovered notable differences in the efficiency of MFIs depending on the type of ownership.

Kumar and Sensarma (2017) discovered that while the age of the MFI is linked to higher inefficiency, profitability, scale, and leverage appear to promote efficiency in their study of the efficiency of microfinance institutions in India using a stochastic distance function approach. According to Kar and Deb (2017), the average technical efficiency of MFIs is estimated to be 79 percent under the BCC model and 98 percent under the

Undesirable Measure Model. If Indian MFIs can reduce their bad output (proxied by Portfolio at Risk 30) to about 14 percent, they will be able to reach the production frontier. Additionally, they confirm that sustainability positively impacts efficiency (as measured by operational self-sufficiency).

Surender (2018) assessed the technical efficiencies of 55 MFIs in India using the stochastic production frontier approach. This approach includes a model for the effects of technical inefficiencies such as administrative and financial expenses, borrowers per loan officer, female loan officers, cost per borrower, and operating expenses for the 2014–15 fiscal year. The average technical efficiency of MFIs was 59%, suggesting that microfinance institutions may raise their output (gross loans) by 41% without increasing the amount of inputs. The individual technical efficiency scores of the sampled microfinance firms varied widely, ranging from 16 to 99 percent.

Ferdousi (2020) analyzed to determine the effectiveness of different Microfinance Institutions (MFIs) in Bangladesh both before and during the establishment of the Microcredit Regulatory Authority (MRA). Using Data Envelopment Analysis (DEA) and the Malmquist Productivity Index approach, he found that seven enterprises were promoted from inefficiency to efficiency and that the average productivity of 35% of firms increased significantly following the implementation of microfinance regulations.

Agostinho and Gaspar (2021) assessed the social and financial efficacy of eight member countries of the Southern African Development Community (SADC) in 2016 by examining 18 microfinance institutions (MFIs). Using an input-oriented manufacturing method, they discovered that offering financial services to women or the entire underprivileged population is profitable and that financial efficiency scores are greater than social efficiency.

In Umasri and Malarvizhi's (2022) study, the technical efficiency of microfinance institutions (MFIs) in South Asia was measured, and their drivers were identified. Two input variables, personnel cost per borrower and gross loan portfolio, were used as output variables along with 13 explanatory factors. They discovered that the likelihood ratio was significant and positive in South Asia. The mean technical efficiency of MFIs in South Asia over the last five years was 31%, 34%, 37%, 40%, and 43%, respectively. Out of 150 MFIs in South Asia, only seven were classified as very efficient (Technical Efficiency values ≥ 70%).

Ali and Nasir (2023) depicted the efficiency of microfinance banks and institutes, as their primary focus is to make the country prosperous by lending loans to the people, as it has consumed fewer days to grant loans, which creates self-employment in Pakistan. Olufolahan et al. (2023) suggested that microfinance banks should implement appropriate lending strategies, such as proprietary lending technologies and effective risk-based oversight, to tackle the significant credit risks related to business lending to improve their efficiency in South-West Nigeria. Baltas and Linares-Zegarra (2024) discovered that microfinance institutions (MFIs) that operate more efficiently tend to exhibit superior financial risk management practices in three key areas: asset quality, capital, and liquidity.

Review of Microfinance Institutions in Nepal

A study conducted by Regmi (2013)found that preserving women's savings and credit groups, understanding the context of poverty and its vulnerability, the process by which members' households accumulate and interact with their livelihood assets, and combining livelihood activities with the use of livelihood assets to maximize income and minimize vulnerability are all important steps toward reducing poverty in Nepal. According to Dhungana (2018), the main problems faced by Nepalese microfinance institutions are multiple financing issues, a lack of adequate financial education and entrepreneurship skills for clients, high interest rates, a high concentration of MFIs in urban and suburban areas, unhealthy competition among MFIs, a lack of an inclusive financial system, poor financial inclusion, and inadequate basic infrastructure.

Karn (2018) discovered that MFIs face several difficulties, including limited resources, unhealthy competition, seasonal migration, political ignorance, exclusion of disadvantaged populations, threats to financial discipline, and poor understanding of microfinance organizations. According to Shrestha (2020), COVID-19 has significantly impacted microfinance institutions. Nonetheless, they made it through the review period with NRB policy measures and a modicum of resilience. The number of past-due borrowers is increasing, indicating that the spread of COVID-19 is ongoing and that there are still adverse risks.

Subedi and Karki (2022) investigated the interplay between MFIs' sustainability and depth and found a sizable trade-off. Chaulagain and Lamichhane (2022) showed a substantial relationship between MFI performance, information technology, loan lending procedures, and regulatory environment. They also find that the success of MFIs is positively correlated and significantly impacted by the loan lending system, regulatory framework, information technology, staff motivation, management system, and efficient risk management.

Research Gap

Different results in the efficiency score using data envelopment analysis (DEA) and stochastic frontier analysis (SFA) in an international context were revealed by a study of the microfinance sector (Abdulai & Tewari, 2016; Annim, 2012; Kipesha, 2012; Riaz & Gopal, 2015; Singh et al., 2013; Umasri & Malarvizhi, 2022). There are differing opinions on how to assess efficiency, define inputs and outputs, and produce consistent results (Bassem, 2008; Gutiérrez-Nieto et al, 2009; Haq et al., 2010; Kipesha, 2013; Kumar & Sensarma, 2017; Surender, 2018). Research on the effectiveness of microfinance organizations is not in agreement. There are variations in the model definition and the types and nature of the variables included. In Nepal, different studies have been conducted on the challenges, problems, and performance of microfinance institutions (Chaulagain

& Lamichhane, 2022; Dhungana, 2018; Karn, 2018; Regmi, 2013; Shrestha, 2020; Subedi & Karki, 2022). The estimation of technical efficiency of Nepalese MFIs is not conducted in the existing literature, which is the study area gap, and the stochastic frontier analysis to estimate technical efficiency, which is the methodology gap for the study. Thus, measuring technical efficiency in Nepalese MFIs is necessary to study their level of resource mobilization.

Methodology

Research Design

This study employed a descriptive and explanatory research design. The output-oriented method was used to measure technical efficiency. A production function was also utilized in this study. A stochastic frontier approach (SFA) is applied. Microfinance institutions primarily target the impoverished, often requiring no collateral and having goals beyond profit maximization. This study adopts an intermediation approach because MFIs' essential services facilitate microcredit, loans, and asset management. The gross loan portfolio (outstanding loans, including all outstanding principal due for all outstanding client loans) is taken as the output variable. Total assets (assets listed on the asset side of the balance sheet), number of employees (individuals who are actively employed in the MFIs), and cost per borrower (operating expenses per active borrower) are used as input variables.

Nature and Sources of Data

The study used panel data from 24 microfinance institutions from 2016/17 AD to 2022/23 AD, totaling 168 observations. The data and other necessary information were collected from the audited annual reports of microfinance institutions and the Nepal Rastra Bank.

Population and Sample Size

Fifty-seven microfinance institutions operate in Nepal (NRB 2023). Of these, 24 retail lending microfinance institutions established before 2016 AD were selected based on the availability of panel data for the period 2016/17 AD to 2022/23 AD. Therefore, convenience sampling was used to select the sample. The list of sampled microfinance institutions is as follows.

Table 1

List of Microfinance Institutions Used in the Study

SN	Name	SN	Name
1	Nirdhan Uthan	13	Gurans
2	Deprosc	14	Swabhiman
3	Chhimek	15	Janauthan

4	Swabalamban	16	Samudaek
5	Nerude	17	Vijaya
6	Swarojgar	18	Mero
7	Laxmi	19	Infinity
8	Civil	20	Grameen
9	NMB	21	Ganapati
10	Forward	22	Sabaiko
11	Mithila	23	Asha
12	Support	24	NADEP

Model Specification

A stochastic production frontier model was used in this study. The SFA modelling framework of this study is as follows:

The production function is

$$\ln y = \alpha_0 + \sum_{i=1}^{n} a_i \ln x_i + E_i$$

Where y is the output variable for the production function, Xi is the vector of quantities of the i variable inputs, and Ei is the stochastic error term, where Et = Ut − Vt is the production function (Mokhtar, Abdullah & Habshi, 2006).

Technical efficiency (TE) can be measured in two ways. If TE is an output-oriented metric, it represents the capacity of a microfinance organization to produce as much as possible given its input sets. Conversely, an input-oriented TE measure indicates how much a microfinance organization may reduce its inputs to produce a particular set of outputs. When the value is 1, everything operates at maximum efficiency on the production frontier. A value below one indicates operations that occur below the boundary. Technical efficiency is represented as a wedge between one and the observed value.

The stochastic frontier model for technical efficiency is given below:

lnGLPit = β0 + β1 lnTAit + β2lnCPBit + β3lnHMit+ Vit - Uit

Where,

lnGLPit represents the natural logarithm of all outstanding principal due to all outstanding client loans of the i-th microfinance institution at period t. This includes current, delinquent, and renegotiated loans but not loans that have been written off. It does not include interest receivables.

lnTAit represents the logarithm of total assets measured in INR of the i-th microfinance institution at time period t.

lnCPBit represents the logarithm of cost per borrower (operating expense/number of active borrowers) measured in rupees of i-th microfinance institution at time period t.

lnHMit represents the logarithm of the number of employees (total number of staff members) of the ith microfinance institution in time period t.

βi represents the parameter to be estimated.

Vit is assumed to be an independent and identically distributed random error that has a normal distribution with mean zero and unknown variance σv^2.

Uit are non-negative random variables associated with the technical inefficiency of production. They are assumed to be independently distributed, and Uit is obtained by truncating (at zero) the normal distribution with mean and variance σ^2.

Theorization

Technical efficiency is the capacity to achieve cost, revenue, or profit efficiency in a given system by either increasing output quantities proportionately without changing input quantities (output-oriented), or decreasing input quantities proportionately without changing output quantities (input-oriented) (Masood & Ahmad, 2010; Coelli et al., 1998). As noted by Coelli et al. (1998), the input-oriented technical efficiency measures answer the following question: "To what extent can input quantities be proportionately reduced without affecting the output quantities produced?" Conversely, the output-oriented measurements of technical efficiency address the question of "How much can output quantities be proportionally expanded without altering the input quantities used?".

Results and Discussion

Status of Bank and Financial Institutions

The status of banks and financial institutions in Nepal comprises commercial banks, development banks, finance companies, microfinance institutions, and infrastructure development banks. The number of commercial banks, development banks, and finance companies decreased over the study period from FY 2016/17 to 2022/23 (Table 2).

Table 2

Number of Banks and Financial Institutions

Category	2016/17	2017/18	2018/19	2019/20	2020/21	2021/22	2022/23
Commercial Banks	28	28	28	27	27	26	20
Development Banks	40	33	29	20	18	17	17
Finance Companies	28	25	23	22	17	17	17
Microfinance Institutions	53	65	90	85	70	65	57
Infrastructure Dev. Banks	0	0	1	1	1	1	1
Total	179	149	170	155	133	126	112

Note. This is taken from the Bank Supervision Report of the Nepal Rastra Bank, 2023.

The number of microfinance institutions increased up to FY 2018/19 AD, and then after, it also showed a decreasing trend. Currently, there are 112 banks and financial institutions in Nepal. Of these, 50.89% represent microfinance institutions (57 microfinance institutions) of Nepal's total number of banks and financial institutions.

Growth of Microfinance Financial Institutions

The growth of microfinance institutions can be studied in terms of the number of MFIs, branches, total human resources, total assets, total borrowers, total loans, and advances in MFIs. The number of MFIs increased from 53 in FY 2016/17 to 90 in FY 2018/19. The number of MFIs decreased to 57 in FY 2022/23 (Table 3). Owing to the merger and acquisition policy of the Nepal Rastra Bank, the number of MFIs is decreasing.

Similarly, the total assets (size) of MFIs also show an increasing trend from Rs. 134 billion to Rs. 508 billion over the study period. Likewise, the growth of MFI branches increased from FY 2016/17 AD to FY 2021/22 AD. However, it decreased from 520 branches (FY 2021/22 AD) to 508 (FY 2022/23 AD).

Human resources increased from 9602 to 22493 during the study period. Likewise, the number of borrowers also increases to FY 2021/22. The loan and advance of MFIs increased from Rs. 106 billion to Rs. 432 billion during the study period.

Table 3

Growth of Microfinance Financial Institutions

Name of MFIs	2016/17	2017/18	2018/19	2019/20	2020/21	2021/22	2022/23
Number	53	65	90	85	70	65	57
Total Assets (Rs. in billions)	134	176	273	325	446	520	508
Branches	1,895	2,450	3,547	4,057	4,685	5,135	5,128
Human Resource	9,602	11,557	17,362	19,017	20,872	23,303	22,493
Borrower (No. in thousands)	1,633	1,853	2,680	2,783	2,992	3,303	2,984
Loan and Advances (Rs. in billions)	106	146	235	263	366	450	432

Note. It is taken from the Bank Supervision Report of Nepal Rastra Bank, 2023.

Impact of Total Asset, Human Resource, and Cost per Borrower on Gross Loan Portfolio

The regression result, taking gross loan portfolio as the dependent variable and total assets, human resources, and cost per borrower of sampled MFIs were determined using the time-invariant inefficiency model in the STATA (Statistics/Data Analysis) program. The stochastic frontier model is run for panel data in STATA (Statistics/Data Analysis) version 14.2, taking the natural logarithm of the gross loan portfolio. Total assets, human resources, and cost per borrower were taken as the Panel ID variable, and year was taken as the time variable for the dataset. Panel data of 24 groups (MFIs) of seven years with 168 observations from the Excel spreadsheet were imported into the STATA software.

Table 4

Regression Result using Time-invariant Inefficiency Model

	Coeff.	Std. Err.	z	P > |z|
Total Assets	0.3672	0.1132	3.24	0.001
Human Resource	0.1929	0.1805	6.61	0.000
Cost Per Borrower	0.8757	0.1275	6.87	0.000
Constant	0.0465	1.8887	0.02	0.980
/mu	-5.4323	49.6302	-0.11	0.913
/lnsigma2	0.6518	7.1035	0.09	0.927
/ilgtgamma	2.0658	7.9781	0.26	0.796
Sigma2	1.9189	13.6312		
Gamma	0.8875	0.7963		
Sigma_u2	1.7031	13.6261		
Sigma_v2	0.2158	0.0262		
Log likelihood = -122.2783, wald chi2 (3) = 867.27 (p > 0.000)				

Note. It is calculated from STATA 14.2 Version using the frontier model, taking the gross loan portfolio as the dependent variable.

After iteration 17, the value of the log likelihood is -122.27837, and wald chi2 (3) is 867.27 (chi2(3) > 0.0000), which indicates that the model is fitted (Table 4). The relationship between inputs and output (Kumbhakar, Wang & Horncastle, 2015) in this study can be expressed as y= f(x), where y represents the output (i.e., gross loan portfolio) and f(x) represents the inputs (i.e. total assets, human resources, and cost per borrower). Therefore, the gross loan portfolio is a function of total assets, human resources, and the cost per borrower. Theoretically, total assets, human resources, and cost per borrower are positively related to gross loan portfolio (output). The regression results also confirmed this relationship, as expected. The computed Wald chi2(3) is 867.27, which is higher than the table value, indicating the presence of a regression. The coefficients of all variables are jointly and not equal to zero. The coefficients of all variables included as independent variables positively affect output.

Other things remain the same: 1 percent change in total assets leads to an increment of 0.36% in the gross loan portfolio (Table 4). The z value of capital is 3.24, and the p-value is 0.001, indicating that total assets are positively significant at the 5 percent significance level.

Other things remain the same: 1 percent change in human resources leads to an increment of 0.19 percent in the gross loan portfolio. The human resource is also positively significant at a 5 percent significance level (P > |z|, i.e., 0.000 > 0.05). Regarding cost per borrower, 1 percent of human resource cost leads to a 0.87 percent increase in the gross loan portfolio. The z value and p value of cost per borrower are 6.87 and 0.000, respectively, i.e., P > |z|, which indicates that the cost per borrower is confirmed with a positive relation of significance at the 5 percent level. Therefore, the alternative hypothesis is that all variable inputs of total assets, human resources, and cost per borrower significantly impact on loans and advances of Nepalese MFIs.

A Gamma value of 0.8875 indicates that 88.75% of the total variance is attributed to inefficiency effects rather than random noise, indicating that inefficiency significantly explains variations in the gross loan portfolio. These findings indicate inefficiency as the primary cause of gross loan portfolio volatility.

Technical Efficiency at the Individual Level

Using the data collected from the MFIs, the efficiency of all MFIs was measured using a stochastic production frontier.

Table 5

Technical Efficiency of Individual Microfinance Institutions

SN	Name	TE Score	SN	Name	TE Score
1	Nirdhan Uthan	64.1	13	Gurans	92.83
2	Deprosc	88.45	14	Swabhiman	89.26
3	Chhimek	78.21	15	Janauthan	82.19
4	Swabalamban	80.1	16	Samudaek	80.37
5	Nerude	61.75	17	Vijaya	84.39
6	Swarojgar	82.01	18	Mero	78.46
7	Laxmi	80.75	19	Infinity	79.73
8	Civil	76.47	20	Grameen	31.1
9	NMB	65.26	21	Ganapati	65.92
10	Forward	88.95	22	Sabaiko	52.82
11	Mithila	93.12	23	Asha	87.44
12	Support	94.59	25	NADEP	85.77
Average TE Score = 77.76					

Note. It is calculated from STATA 14.2 Version using post estimation after the frontier model.

Table 5 shows the Technical Efficiency scores of individual MFIs with an average technical efficiency of 77.76 Percent. The most efficient MFI is Support MFI with a TE score of 94.59%, and the least efficient MFI is the Grameen Bikash MFI with a TE score of 31.10%. Of the 24 sampled MFIs, the TE of 17 MFIs is higher than the average efficiency, 77.76%, and the rest is less than the average efficiency.

Technical Efficiency on Age, Branch Size, and Area Coverage

The average technical efficiency with more than 10 years of operation was 78.22%, and the average technical efficiency with up to 10 years was 76.92% (Table 6). This indicates that older MFIs are more efficient than newer ones.

Table 6

Technical Efficiency on Age, Branch Size and Area Coverage

Basis	Category	No. of MFIs	Average TE
Age group	More than 10 Years of Age	10	78.72
	Up to 10 Years of Age	14	76.92
Branch Size	Having more than 100 Branches	11	73.21
	Having less than 100 Branches	13	81.22
Area Coverage	National Level	18	73.98
	Province Level	4	92.45
	District Level (10-19 Districts)	2	81.28

Note. It is calculated from STATA 14.2 Version using post estimation after the frontier model.

The average technical efficiency of MFIs with more than 100 branches was 73.21%, and that of MFIs with fewer than 100 branches was 81.22%. This indicates that a microfinance institution with fewer branches is more efficient than an MFI with more branches.

MFIs with their area coverage can be classified into national, provincial, and district levels (10 -19 districts). Out of 24 MFIs, 18 operate at the national level, 4 MFIs operate at the provincial level, and 2 MFIs operate at the district level, with 10 to 19 districts. The average technical efficiency of the national-level MFIs was 73.98 percent. Similarly, the average technical efficiencies of province- and district-level MFIs were 92.45 percent and 81.28%, respectively.

The average technical efficiency of province-level MFIs (92.45 percent) was higher than that of national-level MFIs (73.98 percent) and district-level MFIs (81.28 percent). This indicates that province-level MFIs successfully provide gross loan portfolios by properly utilizing their assets, human resources, and operating expenses related to their net active borrowers, compared to national—and district-level MFIs.

Microfinance Institutions at Various Levels of Efficiency

Among the 24 MFIs, one lies below the 50 percent efficiency level, five lie between the 50 percent and 70 percent efficiency levels, 15 lie between the 70 percent and 90 percent efficiency levels, and three lie above the 90 percent efficiency level. This shows that most MFIs operate at 70 percent to 90 percent efficiency.

Table 7

Microfinance Institutions Operating at Various Levels of Efficiency

Basis	Efficiency Score	No. of MFIs	Average TE in %
Efficiency in %	Below 50%	1	31.1
	50 % to 70%	5	61.95
	70 % to 90 %	15	82.84
	Above 90 %	3	93.52

Note. It is calculated from STATA 14.2 Version using post estimation after the frontier model.

Discussion

The average technical efficiency score of Nepalese MFIs is 77.76%, which indicates that Nepalese MFIs are unable to utilize their resources by 22.24% and can improve their efficiency to maximize resources. The TE score of 77.76 percent is higher than the findings of studies conducted by Abdulai and Tewari (2016), Annim (2012), Gebremichael and Gassesse (2016), Olasupo and Afolami (2013), Oteng-Abayie et al. (2011), Oteng-Abayie et al. (2016), Singh et al. (2013), Surender (2018), and Zerai and Rani (2012), but less than the findings of studies conducted by Kar and Deb (2017), Kipesha (2012), Riaz and Gopal (2015), and Umasri and Malarvizhi (2022).

The technical efficiency of MFIs with more than 10 years of operation is greater than that of MFIs with up to 10 years, which indicates that older MFIs are more efficient than newer MFIs. MFIs with fewer branches (less than 100 branches) were more efficient (81.22 percent) than MFIs with a greater number of branches (more than 100 branches), which were less efficient (73.21 percent). The highest percentage of technical efficiency was 92.45 percent at the province level, followed by district-level MFIs (81.28 percent) and national-level MFIs (73.98 percent). This indicates that province-level MFIs successfully provide gross loan portfolios with proper utilization of their total assets, human resources, and operating expenses related to their net active borrowers, compared to national- and district-level MFIs. This may cause lower coverage, and more focus on the activities helps increase the efficiency of MFIs.

Most MFIs (15 out of 24) run at a 70% to 90% efficiency level with an average TE of 82.84%, which indicates that most Nepalese MFIs can increase their efficiency to maximize resource utilization.

Conclusion

In conclusion, the coefficients of all the variables included as independent variables, such as total assets, human resources, and cost per borrower, positively affect the output, that is, the gross loan portfolio. Total assets, human resources, and cost per borrower significantly impact loans and advances of Nepalese MFIs. This indicates that the gross loans and advances to MFIs ' borrowers in Nepal are determined by their skilled employees and the size of the MFIs.

The average TE of the MFIs is 77.76%, which indicates that the input wastage of the MFIs is 22.24%. Thus, the policy of MFIs to utilize their resources should be improved in terms of optimal management. Microfinance institutions with fewer branches are more efficient than MFIs with more branches. Therefore, the policy of larger (in terms of branches) MFIs allocating resources in branches should be improved by focusing on branch-wise performance through proper resource utilization. The coefficient of human resources as an input for the gross loan portfolio is only 0.19. Therefore, there is a need for appropriate training and development for employees, rewards for the best job performance, and good workload management in Nepalese MFIs to make more skilled human resources to increase the efficiency of Nepalese MFIs.

The Gamma value of 88.75% strongly suggests that inefficiency is the primary source of variability in gross loan portfolios. Inadequate asset use, poor management techniques, or structural problems with MFIs could cause this inefficiency.

To maximize resource mobilization, Nepalese microfinance institutions can minimize their wasted resources, which may be the basis for increasing micro entrepreneurs providing quick lending, diversified utilization, close monitoring, and technical assistance to Nepal's deprived and poor people. Therefore, this study has important implications for policymakers of microfinance institutions to utilize their resources to improve the efficiency of microfinance institutions in Nepal.

This study mainly focuses on the technical efficiency of Nepalese MFIs using SFA. Taking panel data of 24 microfinance institutions (established before 2016 AD) covering 7 years period from 2016/17 AD to 2022/23 AD, the study has used production function, intermediation approach and output oriented with gross loan portfolio as dependent variable and total asset, human resource and cost per borrower as independent variables. There are multiple borrowers for MFIs. The number of borrowers provided by individual MFIs may not be complete, as they include their borrowers. Further research can be conducted in other areas of MFIs using more analytical methods and variables than those employed in this study.

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Conflict of Interest

The authors have no conflict of interest in the research work.

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