Iranian Journal of Economic Studies, 12(2) 2023, 369-406

Shiraz University

Iranian Journal of Economic Studies

Journal homepage: ijes.shirazu.ac.ir

The Impact of Private Sector Credit on Self-Employment in Iran: A Hybrid Approach of Artificial Intelligence with Spatial Model

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Article History

Received date: 18 December 2024
Revised date: 17 January 2025
Accepted date: 23 January 2025
Available online: 07 February 2025

JEL Classification

G21
G28
J24
O33
R15

Keyword

Access to Finance
Artificial Intelligence
Applications
Self-Employment
Spatial Analysis
Microfinance

Abstract

Self-employment plays an important role in the Iranian economy and understanding the factors that influence it is of great importance. The aim of this study was to investigate the repercussions of private sector credit on self-employment in Iran. Artificial intelligence techniques such as artificial neural networks, deep neural networks and machine learning algorithms were used to identify non-linear relationships and complex patterns in the data. Spatial econometric models such as SAR, SEM and SDM were also used to account for spatial dependencies between provinces and to examine the spatial spillover effects of utilization for the period 1990-2023 at the provincial level of the country.

The results indicate a negative and significant relationship between the ratio of microfinance to gross domestic product (GDP) and the self-employment rate. The negative coefficients of economic openness index and capital formation rate also indicate their negative impact on self-employment. In contrast, the total factor productivity and education expenditure variables have a positive and significant effect on the self-employment rate. The results of the spatial models also show the interdependence of the self-employment rate in the different regions of the country.

Although microfinance was expected to increase self-employment, this study found a negative relationship between the two, which could be due to inefficiencies in the provision of microfinance and its insufficient focus on the creation of sustainable and productive jobs. Greater economic openness and higher capital formation rates also have a negative impact on self-employment, as they increase foreign competition and encourage investment in larger sectors of the economy. On the flip side, improvements in total factor productivity and investment in education form the basis for the growth of self-employment. The results of the spatial models also underline the importance of considering spatial spillover effects and dependencies when formulating measures to promote employment and entrepreneurship.

Highlights

- Private sector credit negatively impacts self-employment rate in Iran, contrary to expectations.
- Economic openness and capital formation rate show negative effects on self-employment.
- Total factor productivity and education expenditure positively influence self-employment.
- Spatial models reveal interdependence of self-employment rates across Iranian provinces.

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DOI: 10.22099/ijes.2025.51966.1985

1. Introduction

Entrepreneurship is a key goal in the development and education of societies, helping to address challenges and improve the quality of life, as well as the growth and advancement of communities (Dabbous et al, 2023). Thus, cultivating high-quality human resources capable of creativity and innovation is crucial for a country's economic and industrial growth (Dabić et al, 2023). Given the significance of work and entrepreneurship, along with the country's youthful population, it is essential for the education system to recognize and nurture entrepreneurial skills and instill a culture of work and entrepreneurship among adolescents and young adults (Boldureanu et al, 2020). The labor market plays a vital role in the economy due to its impact on various aspects, including economic, political, and cultural conditions, and its interaction with other economic markets (Fassmann, 2001).

In Iran, the labor market is currently imbalanced (Amini, 2015), with labor supply exceeding demand (Mohammadi et al, 2019). This imbalance has led to rising unemployment, which continues to worsen (Hallaji et al, 2024). The increasing gap contributes to a crisis of unemployment and a lack of suitable job opportunities, particularly for young people and university graduates (Virk et al, 2023). Self-employment has become a crucial focus in labor market policies worldwide (Blau et al, 1999), as self-employment and microcredit programs aim to tackle unemployment. Self-employed individuals, such as doctors, shop owners, and small manufacturers, sustain themselves through their own businesses rather than receiving wages from others (McKernan, 2002).

Many countries have successfully created new job opportunities in the self-employed sector through support programs, which often include social assistance like counseling and financial aid in the form of microcredit or small business financing (Cho et al, 2016). To reduce unemployment and generate necessary job opportunities, substantial financial resources are required, which can be achieved through increased investment and banking support for self-employment (Thurik et al, 2008). Experiences from developed nations demonstrate that their financial markets have evolved alongside economic growth, positively influencing long-term development (Arestis et al, 1997). Thus, financial support is crucial for enhancing self-employment (Hariram et al, 2023).

While state-owned banks are the primary source of financial support for businesses in Iran, the private banking sector has emerged as a significant contributor to economic outcomes (Rashidardeh et al, 2017). Private banks offer operational flexibility and profit-driven incentives, allowing them to respond quickly to market demands. They create tailored financial products for two main groups: entrepreneurs and self-employed individuals. These offerings may include specialized loans, financial advisory services, and investment instruments designed for their specific needs (Dashtban Farooji, 2015). This credit enables entrepreneurs and self-employed individuals to implement their ideas, grow their businesses, and create new job opportunities. Access to adequate financing is critical for the success of startups and self-employed ventures. Without it, these businesses face challenges such as securing initial capital, covering ongoing expenses, launching new products, and attracting customers. Financial constraints can hinder growth and even lead to business failure. Therefore, providing sufficient credit is vital for helping these groups navigate the startup phase, achieve sustainable growth, and thrive in a competitive market. Private sector credit facilitates self-employment and fosters the creation of new businesses, contributing to increased employment and economic prosperity while reducing unemployment (Ata-Agboni et al, 2024). Moreover, access to private sector credit allows the self-employed to enhance their business performance, adopt new technologies, and improve competitiveness, ultimately ensuring the sustainability and long-term growth of small enterprises (Abbas et al, 2024).

Researching The repercussions of private sector credit on self-employment in Iran is essential for several reasons. First, with high unemployment rates, particularly among youth and graduates, promoting self-employment can effectively create jobs and alleviate unemployment, aligning with Iran's economic and social development objectives. As the country seeks to diversify its economy and reduce reliance on oil revenues, fostering the private sector and entrepreneurship becomes increasingly important. However, financial constraints remain a significant barrier to starting new businesses, making it crucial to investigate the role of private sector credit in enhancing self-employment. This research can offer insights into optimizing lending practices to support entrepreneurs and expand self-employment opportunities. Given the government's limited financial resources and state banks' inability to meet the diverse needs of entrepreneurs, leveraging the private sector's capabilities in financing self-employment is vital. By exploring the influence of private sector credit on self-employment, this research can help identify strategies to strengthen the entrepreneurial ecosystem and promote sustainable economic growth. Ultimately, the primary aim of this study is to assess The repercussions of private sector credit on self-employment within the Iranian economy.

The future structure of the article will include sections on literature and research background, methodology (including research method and research model), research results, and conclusions and suggestions.

2. A Review of the Related Literature

Loans to the private sector are a crucial financial tool that significantly contributes to economic development and job creation (Olowofeso et al, 2015). Economic theories suggest that access to credit helps entrepreneurs overcome financial obstacles and opens up new self-employment opportunities (Willis et al, 2020). Self-employment is a vital means of reducing unemployment and encouraging economic participation (Narita, 2020). It refers to individuals creating jobs and earning income independently, without working for someone else (Le, 2002). The literature indicates a strong connection between private sector credit and self-employment, as private financing is essential for supporting entrepreneurial activities (Menon & Rodgers, 2013).

Schumpeter's theory highlights innovation as a key driver of economic growth, with credit identified as a motivating factor for entrepreneurs (Sundbo, 2015). Schumpeter argued that banks and financial institutions facilitate the realization of innovative ideas and the establishment of new firms through lending (Beaugrand, 2004; McDaniel, 2005). Empirical evidence supports the notion that access to credit is crucial for the success of small and medium-sized enterprises and for boosting self-employment rates (Evans & Jovanovic, 1989). For instance, increases in lending to the private sector across various nations have corresponded with higher self-employment and entrepreneurship rates (Acs & Szerb, 2007). Additionally, lending is vital not just during the startup phase of businesses but also for their growth and development, enabling entrepreneurs to invest in new technology, enhance products and services, and expand markets (Beck et al, 2008). However, limited access to credit remains a significant hurdle to self-employment and entrepreneurship, particularly in developing nations with weaker financial systems (Klapper et al, 2006).

According to economic theories, access to financing is one of the primary challenges for entrepreneurs (Muñoz-Céspedes et al, 2024). Classical and neoclassical theories stress that well-functioning financial markets are key for effective capital allocation and economic growth (Mohamed et al, 2019). In this light, private sector credit reduces transaction costs and facilitates investment, thereby increasing production and employment (Alfaro et al, 2003). Access to credit unleashes new opportunities for self-employment and mitigates financial barriers for entrepreneurs (Herkenhoff et al, 2021). Additionally, human capital theory posits that self-employment allows individuals to utilize their skills and knowledge, enhancing their productivity and income. In this context, private loans support success in self-employment by funding education and skills development (Eide & Showalter, 2021).

Economic models like Lucas's model (1978) explore the decision-making process of whether to work for others or become self-employed, with access to capital being a critical factor (Kim, 2007). If individuals lack the financial means to start a business, they are more likely to opt for traditional employment. Thus, private credit can enhance self-employment rates by easing access to financial resources (Salas et al, 2014). From an institutional perspective, private lending is shaped by laws, regulations, and financial institutions. Strengthening institutional frameworks and creating a stable, predictable environment can foster the development of credit markets and improve access to financial resources, thereby promoting entrepreneurial endeavors (Barba-Sánchez & Atienza-Sahuquillo, 2017).

Endogenous growth models, such as Romer's model (1990), highlight that investments in research and development (R&D) and innovation can drive sustainable economic growth (Gancia & Zilibotti, 2005). Within these models, private sector credit is essential for financing entrepreneurs' innovative activities. Access to affordable and sufficient financing acts as a motivation for innovation and self-employment. Financial development theories assert that building efficient financial systems leads to better resource allocation and poverty alleviation (Uiku, 2004). These theories suggest that private loans can assist low-income individuals, including those without adequate collateral, in starting small businesses (Looi Kee & Chen, 2005). Research indicates that financial development and expanded credit services can enhance self-employment opportunities and reduce inequality.

In summary, private sector credit is vital for fostering self-employment by funding investments, lowering financial obstacles for entrepreneurs, promoting innovation, and developing human capital (Abiola et al, 2020). Improving credit access and establishing robust institutional frameworks can increase employment opportunities and alleviate unemployment through self-employment (Du & Nguyen, 2019). Therefore, enhancing financial markets and boosting credit to the private sector, alongside improving the business environment, can support the growth of self-employment and economic development in Iran. Consequently, numerous studies globally have explored this subject, summarized in Table 1.

Table 1. Related studies

Researchers	Objective	Key Findings
Tayyibi & Abbaslou (2009)	Bank credit's impact on Iran's business environment	Bank credit significantly boosts employment by facilitating producer investment.
Saeedi (2012)	Bank loans and employment in Golestan, Iran	Non-mandatory loans positively affect employment more than mandatory loans.
Sohaili et al. (2018)	Public vs. private investment and employment in Iran	Private investment positively impacts employment; public investment negatively impacts it.
Pham et al. (2018)	Financial development and entrepreneurial well-being (China, Ukraine, Russia)	Entrepreneurial well-being is higher than employee well-being in China and Russia; the relationship with financial development varies by country.
Caraher & Reuter (2019)	Financial literacy and self-employment	Positive correlation between financial literacy and self-employment.
Kananurak & Sirisankanan (2020)	Financial development and self-employment	Financial institutions negatively affect self-employment; financial markets show no significant effect.
Herkenhoff et al. (2021)	Consumer credit access and self-employment	Increased credit access leads to higher rates of self-employment and business ownership.
Effiong et al. (2022)	Private sector credit and unemployment in Nigeria	Long-run link exists, but private credit's impact on unemployment is insignificant in both short and long run.
Hassanali & Nasir (2024)	Microfinance banks vs. institutions for self-employment in Pakistan	Microfinance banks are more effective at creating self-employment.
Kunawotor & Ahiabor (2024)	Self-employment, financial access, and well-being in Africa	Self-employment negatively, financial access positively impacts well-being; interaction shows synergistic effect.
Abdulraqeb & Shahin (2024)	Access to finance and self-employment in Saudi Arabia	Innovation, not access to finance, significantly boosts self-employment.
Hoseinpour Naderi & Alijani (2024)	Bank credit and agricultural employment in Iran	Bank credit positively affects agricultural employment; state-owned banks have greater impact.
Sarani et al. (2024)	Microcredit and rural livelihoods in Zabol County, Iran	Microcredit, especially employment loans, positively impacts rural livelihoods.

Kannapalan (2024)	Self-employment loans and livelihood improvement	Self-employment loans improve livelihoods and income, though the average increase is modest.

Source: *Research Findings*

This research offers a novel examination of the repercussions of private sector credit on self-employment in Iran, utilizing a combined approach that integrates artificial intelligence and spatial modeling. This innovative methodology has not been previously explored at either the national or international levels. A key feature of this study is its application of artificial intelligence techniques, such as neural networks and machine learning algorithms, alongside spatial models, to analyze the relationship between private sector credit and self-employment. While earlier studies primarily relied on traditional econometric methods, this research introduces a comprehensive framework for understanding the issue.

Moreover, this study uniquely considers the spatial and regional dimensions of private sector credit's effect on self-employment in Iran. By acknowledging the regional disparities in development, access to financial resources, and labor market characteristics, the inclusion of spatial factors in the analysis yields more accurate and practical insights that previous research has overlooked. The current study also leverages extensive and up-to-date data on private sector and self-employment credit at the provincial level over a significant timeframe, providing a clearer picture of the trends and current state of these variables. In contrast, many prior studies have been limited to national-level data or specific timeframes.

Methodologically, this research presents an innovative approach by merging spatial models with artificial intelligence techniques. The spatial models account for regional dependencies and spillover effects in the repercussions of credit on self-employment. Simultaneously, the application of artificial intelligence methods enables the identification of complex, non-linear patterns and relationships between variables that traditional econometric methods may struggle to capture.

In summary, this study addresses the critical issue of how private sector credit influences self-employment in Iran through cutting-edge analytical techniques, marking a significant advancement in understanding this relationship. The findings could inform the development of effective policies aimed at fostering self-employment and entrepreneurship in Iran, leveraging vital credit and private sector resources.

3. The Study Model

Self-employment plays a vital role in Iran's economy, driving both job creation and economic expansion. However, access to financing remains a significant hurdle for individuals pursuing self-employment. Private sector credit offers a potential solution to this challenge, making it crucial to understand its impact on self-employment to inform effective policy interventions. This study investigates the relationship between private sector credit and self-employment in Iran using a novel combined approach. By integrating artificial intelligence and spatial econometrics, we aim to analyze complex, nonlinear relationships while accounting for spatial dependencies and geographical influences. Leveraging comprehensive, current data, this research seeks to provide robust empirical evidence on the role of private sector credit in fostering self-employment within Iran.

The study employs annual time series data from 1990 to 2023, sourced from reputable institutions such as the World Bank, the Central Bank of the Islamic Republic of Iran, the Economic and Financial Data Bank, and the Statistical Center of Iran. Our analysis will leverage a diverse suite of artificial neural networks, including Multilayer Perceptron (MLP), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM) networks, generic Artificial Neural Networks (ANN), Gated Recurrent Unit (GRU) networks, Transformer Neural Networks (TNN), Autoencoders (for dimensionality reduction, akin to PCA), Deep Belief Networks (DBN), Attention-Based Neural Networks, and Graph Neural Networks (GNN). These models excel at capturing nonlinear relationships, identifying spatiotemporal patterns, and generating accurate predictions. Furthermore, machine learning algorithms like Support Vector Regression (SVR), Decision Tree, Random Forest, Gradient Boosting, K-means clustering (note: K-clustering is not a regression method, it is for clustering), Lasso Regression, Gradient Boosting Tree (presumably you mean Gradient Boosted Trees or XGBoost), and Ridge Regression will also be employed.

To address spatial considerations and interprovincial dependencies, spatial econometric models like the Spatial Autoregressive Model (SAR), Spatial Error Model (SEM), and Spatial Durbin Model (SDM) will be utilized. These models will allow us to examine spatial spillover effects and geographical relationships.

By combining the strengths of artificial neural networks and spatial econometric models, this study aims to provide a comprehensive and rigorous analysis of the influence of private sector credit on self-employment in Iran.

- Model specification

Self-employment

Since the main objective of the present study is to investigate the effect of microcredit on self-employment, based on the studies of Ghavidel (2008); Shahabadi et al (2013); Amini Milani et al (2021); Kannapalan (2024); Hassanali and Nasir (2024); Sarani et al (2024), the self-employment index was calculated as follows:

The self-employment to labor force ratio (LFPR) index is one of the most important indicators for measuring the level of self-employment in an economy. This index shows the ratio of the number of self-employed to the total active population (employed and unemployed) and is calculated as follows in equation (1):

$$\mathrm{LFPR} = \frac{\mathrm{SELF}}{\mathrm{LFPR}} \times 100 \qquad (1)$$

In this formula, LFPR represents the self-employment rate to the active population, SE the number of self-employed workers, and LF the active population. This index determines the percentage of people who are self-employed among the active population (Shahabadi et al, 2013). Therefore, the LFPR index is a suitable tool for assessing the repercussions of economic policies and interventions on the self-employment rate. For example, this index can be used to examine the repercussions of microcredit on self-employment (Shahabadi et al, 2013). Because by comparing the LFPR rate before and after granting microcredit, it can be seen whether these microcredits have been able to increase the self-employment rate among the active population or not (Amini Milani et al, 2021). Also, the LFPR index can be used to compare the self-employment rate among different population groups (such as women and men, urban and rural areas) (Ghavidel, 2008). Overall, the self-employment to active population ratio (LFPR) index is an efficient and useful tool for measuring the level of self-employment and evaluating The repercussions of economic policies on it.

To access self-employment data for Iran, you can use the following sources:

The Statistical Center of Iran, as the main source of data on the labor market and employment in the country, provides important information through its website (https://amar.org.ir/statistical-information/catid/2972?title). The World Bank is also known as another reliable source by providing data on self-employment in Iran. By searching for the phrase "Self-employed, total (% of total employment) (modeled ILO estimate) - Iran, Islamic Rep." on the World Bank website (https://data.worldbank.org/), the share of self-employment in total employment in Iran from 1991 to 2021 can be examined.

Central Bank of the Islamic Republic of Iran: Banks' economic information, including statistics on bank credits and bank financing, was used from the banking statistics website (https://www.cbi.ir/simplelist/22697.aspx).

National Statistics System: Information on unemployment rate and other economic parameters was collected from the National Statistics System (https://amar.org.ir/work).

Time Series Bank: Data related to microfinance has been collected from the website (https://tsdview.cis.cbi.ir/single-data).

-Microcredit

Microcredits are small loans that are usually provided to low-income and self-employed individuals so that they can start or develop their own businesses (Taheri Haftasiabi et al, 2024). Therefore, considering the research topic, which is to examine The repercussions of microcredits on self-employment, the "Microcredit to GDP Ratio" (MGR) index was measured as an independent research variable and used to examine self-employment. The method of measuring this index is described in Equation 2 as follows:

$$\mathrm{MGR} = \frac{\mathrm{MC}}{\mathrm{gdp}} * 100 \tag{2}$$

Where:

- MGR: Microcredit to GDP Ratio
- MC: Total amount of microcredit disbursed (in thousand billion Rials)

• GDP: Gross Domestic Product (in thousand billion Rials)

Therefore, the reasons for choosing the MGR index as a microcredit indicator are as follows:

1. This index shows the amount of microcredit disbursed compared to the total economy (GDP). Therefore, it can be seen whether the increase in microcredit has had a significant impact on self-employment on a macroeconomic scale (Imai et al, 2012).
2. The use of this index allows comparisons to be made between different countries or regions. Since GDP is a standard and comparable indicator, the situation of microcredit in Iran can be compared with other countries (Quayes, 2012).
3. The calculation of this index requires macroeconomic data (total amount of microcredit disbursed and GDP), which are usually available. Therefore, the calculation of this index for Iran is possible given the available data (Central Bank of the Islamic Republic of Iran, 2021).

The following sources were used to access data on microcredit in Iran.

(1) Ministry of Cooperatives, Labor and Social Welfare: The website of the Ministry of Cooperatives, Labor and Social Welfare (https://www.mcls.gov.ir/) publishes reports and statistics on employment and entrepreneurship.

(2) Omid Entrepreneurship Fund: Omid Entrepreneurship Fund (https://karafariniomid.ir/) is one of the most important microcredit institutions in Iran.

(3) Central Bank of Islamic Republic of Iran: The Central Bank of Iran (https://www.cbi.ir/) publishes in its reports data on the facilities granted by banks and financial and credit institutions. By searching for the phrase "goodwill loan facilities" or "microcredit facilities", information on the amount of microcredit disbursed by the banking system can be accessed.

- Control variables

1. Total Factor Productivity (TFP): Total factor productivity is an indicator that shows the combined efficiency of production inputs (including labor and capital) in creating economic output. This indicator is calculated using the Malmquist index (Coelli et al, 2005). Data on TFP are collected from the Penn World[1] Table database.
2. Education Expenditure (EDUT): This variable shows the amount of government or private sector spending on education. Education expenditure is usually expressed as a percentage of gross domestic product (GDP) (World Bank, 2021) .Data on education expenditure are collected from the World Bank's[2] World Development Indicators
3. Openness Index (OPEN): This index shows the extent to which a country's economy interacts with the global economy through international trade

[1] https://www.rug.nl/ggdc/productivity/pwt/
[2] https://data.worldbank.org/indicator/SE.XPD.TOTL.GD.ZS?locations=IR

and is calculated as the ratio of total exports and imports to gross domestic product (Frankel & Romer, 1999). It is indexed as equation (3).

$$\mathrm{OPEN} = \frac{\mathrm{Exports+Imports}}{\mathrm{GDP}} \times 100 \quad (3)$$

Data on Iran's exports, imports and gross domestic product are collected from the Central Bank of the Islamic Republic of Iran[1] and the World Bank's World Development Indicators.

4. Capital Formation Rate (CI): This variable shows the rate of investment in fixed assets (such as machinery, equipment, buildings, and infrastructure) as a percentage of GDP (Barro, 1991). Data on the capital formation rate are collected from the World Bank's World Development Indicators.

The use of control variables is very important in economic research, especially in the study of The repercussions of microcredit on self-employment. These variables help the research to examine the effects of other economic factors that may affect the relationship between microcredit and self-employment. Therefore, the consideration of these control variables provides a more accurate picture of the actual impact of microcredit on self-employment (Banerjee et al, 2015). For example, total factor productivity (TFP) is an indicator that shows the overall efficiency of the economy and can affect the level of self-employment. Therefore, by examining this variable, the effect of microcredit on self-employment can be examined separately from the effect of total productivity (Augsburg et al, 2015). In addition, other control variables such as education expenditure (EDUT), openness index (OPEN), and capital formation rate (CI) may in turn affect self-employment. For example, the level of education of individuals can affect their ability to start and run their own business (Becker, 1993). Also, the degree of openness of the economy and access to international markets can expand self-employment opportunities (Frankel & Romer, 1999). In addition, the rate of capital formation indicates the level of investment in the economy, which can affect employment and self-employment opportunities (Barro, 1991). Therefore, by examining these variables, the net effect of microcredit on self-employment can be examined more precisely. Finally, to examine The repercussions of microcredit on self-employment using a combination of artificial intelligence and a spatial econometric model, the following model, known as equation (4), was used.

$$\mathrm{LFPR_i} = \mathrm{F}(\beta_0 + \beta_1 \mathrm{MGR_{it}} + \beta_2 \mathrm{TFP_{it}} + \beta_3 \mathrm{EDUT_{it}} + \beta_4 \mathrm{OPEN_{it}} + \beta_5 \mathrm{CI_{it}} + \rho \sum_{j-1}^{n} \omega_{ij} \mathrm{LFPR_j} + \varphi_{it}) \quad (4)$$

Where:

- LFPRit: Self-employment rate to active population in region i and time t;
- MGRit: Microcredit ratio to GDP in region i and time t;
- TFPit: Total factor productivity in region i and time t;
- EDUTit: Educational expenditure in region i and time t;
- OPENit: Economic openness index in region i and time t;
- CIit: Capital formation rate in region i and time t;

[1] https://www.cbi.ir/page/20949.aspx

- ρ: Spatial autocorrelation coefficient;
- :Wij: Elements of spatial weight matrix indicating the relationship between regions i and j;
- φit is the error term for region i at time t;
- In this model, in addition to the control variables, a spatial autocorrelation term $(+ \rho \sum_{j-1}^{n} \omega_{ij} LFPR_j)$is used to account for the spatial dependence between self-employment rates in different regions. This term indicates that the self-employment rate in one region is also affected by the self-employment rates in neighboring regions.

3.1 Method description

A combination of artificial neural networks and spatial econometric models is used to analyze and investigate the relationship between private sector credit and self-employment in Iran. This combined approach allows the identification of non-linear and complex relationships between variables, the extraction of spatio-temporal patterns, and the provision of detailed analyses. Therefore, the explanation of the methods used in this study is as follows:

Multilayer Perceptron (MLP) Neural Network: A deep learning MLP neural network (Haykin, 2009) will analyze the relationship between private sector credit and self-employment rates in Iran. This model employs interconnected layers of neurons (input, hidden, and output) to process data. Private sector credit-related variables serve as inputs, while the self-employment rate is the output. Training occurs via backpropagation (Rumelhart et al, 1986), optimizing neuron weights to uncover nonlinear relationships. This approach captures intricate data patterns that traditional linear models might overlook. Overfitting is mitigated through techniques like weight adjustment and early stopping (Prechelt, 1998).

Convolutional Neural Network (CNN): While typically used for image processing, a CNN (LeCun et al, 1998) is employed here to analyze spatiotemporal private sector credit and self-employment data. Credit data, structured into matrices representing time and provinces, are processed by convolutional layers to extract local features. These matrices allow the identification of spatiotemporal patterns. Pooling layers then reduce dimensionality while preserving key features (Scherer et al, 2010). Finally, fully connected layers predict self-employment rates based on these extracted features. Performance is enhanced by techniques like dropout and batch normalization (Srivastava et al, 2014; Ioffe & Szegedy, 2015).

Recurrent Neural Network (RNN): An RNN (Elman, 1990), designed for sequential data, will analyze the temporal dynamics of private sector credit's influence on self-employment. Feedback loops within the RNN enable memory retention, facilitating the processing of input sequences and identification of long-term dependencies. Time series data on private sector credit and other economic indicators are input, with the network trained to predict self-employment trends. Gradient pruning (Pascanu et al, 2013) addresses the vanishing gradient problem.

Advanced RNN variants like LSTM and GRU, discussed below, further enhance the model's ability to capture long-term dependencies.

Long Short-Term Memory (LSTM) Neural Network: This advanced RNN architecture (Hochreiter & Schmidhuber, 1997) mitigates the vanishing gradient problem, enabling analysis of private sector credit's long-term impact on self-employment. LSTM's sophisticated gate structure (input, forget, and output) facilitates long-term information retention and irrelevant information discarding. This allows for the exploration of intricate, long-term relationships between private sector credit and self-employment. Sequential time series data are input, training the network to discern complex patterns and predict self-employment trends accurately. Techniques such as dropout within recurrent layers (Gal & Ghahramani, 2016) and hyperparameter tuning via grid search or Bayesian optimization enhance performance.

Artificial Neural Network (ANN): Inspired by the human brain (McCulloch & Pitts, 1943), an ANN models the nonlinear relationship between private sector credit and self-employment. This network of interconnected artificial neurons processes information layer by layer. Input variables include private sector credit, economic indicators, and other relevant factors. Backpropagation trains the network, optimizing connection weights to predict self-employment. Weight tuning (L1 and L2), dropout, and advanced activation functions like ReLU (Nair & Hinton, 2010) enhance performance. Automated methods like grid search or evolutionary algorithms optimize network architecture.

Gated Recurrent Neural Network (GRU): Introduced by Cho et al. (2014), the GRU, an advanced RNN, addresses vanishing and exploding gradient problems, analyzing the temporal effects of private sector credit on self-employment. Its update and reset gates enable long-term information retention and filtering. Time series data are sequentially input, training the network to uncover complex relationships with self-employment. GRU's simpler structure compared to LSTM can offer computational advantages (Chung et al, 2014). Adaptive learning rates and advanced optimizers like Adam (Kingma & Ba, 2014) further refine performance.

Transformer Neural Network (TNN): Originally designed for natural language processing (Vaswani et al., 2017), TNNs, with their attention mechanism, are applied here to analyze the intricate relationship between private sector credit and self-employment. By selectively focusing on critical data components, TNNs effectively model short and long-run dependencies, surpassing traditional RNNs. Time series data are input, and the multi-headed attention mechanism explores complex relationships across different timescales. Techniques such as weight adjustment, dropout, and layer normalization optimize performance. Transfer learning and pre-training address data scarcity (Devlin et al, 2018).

Autoencoder Neural Network: Autoencoders (Hinton & Salakhutdinov, 2006) learn efficient, unsupervised data representations. Here, they reduce dimensionality and extract key features from private sector credit and other economic variables. The encoder compresses input data into a compact representation (code), while the decoder reconstructs the original data from this code. This process extracts hidden patterns and features, which can then be used as input for other self-employment prediction models. Advanced autoencoder variants like denoising autoencoders (Vincent et al, 2008) and variational autoencoders (Kingma & Welling, 2013) enhance robustness and stability.

Deep Belief Neural Network (DBN): Composed of stacked restricted Boltzmann machines (RBMs) (Hinton et al, 2006), DBNs model complex relationships between private sector credit and self-employment. A two-step training process is employed: unsupervised training of individual RBM layers to uncover hidden patterns, followed by supervised fine-tuning of the entire network using backpropagation for self-employment prediction (Bengio et al, 2007).

Attention-based Neural Network: Utilizing the attention mechanism (Bahdanau et al, 2015), this network assesses the relative importance of different private sector credit aspects in influencing self-employment. By assigning varying weights to different features and time periods (Vaswani et al, 2017), the model identifies key influences.

Graph Neural Network (GNN): Designed for graph-structured data (Scarselli et al, 2009), GNNs model the intricate relationships between Iranian provinces concerning private sector credit and self-employment. Provinces represent nodes, and inter-provincial connections (e.g., economic flows, migration) are edges (Kipf & Welling, 2017). This framework captures the spatial dynamics of the relationship under investigation.

Support Vector Regression (SVR): Support Vector Regression (SVR) is a machine learning method that uses the principles of Support Vector Machines (SVM) to solve regression problems (Drucker et al, 1997). In this study, SVR is used to predict the self-employment rate based on variables related to private sector credit and other economic indicators. SVR tries to find a regression function that has the maximum deviation ε from the true values of y for all training data, while being as flat as possible (Smola & Schölkopf, 2004).

Decision Tree: A decision tree is a machine learning model organized in a tree structure (Quinlan, 1986). In this study, decision trees are used to identify key factors in specific loans that affect self-employment. This model, with classifications based on various characteristics, creates decision rules that can be used to predict self-employment (Breiman et al, 1984).

Random Forest: A machine learning algorithm based on a set of decision trees (Breiman, 2001). In this study, a random forest is used to predict the scores of private credit studies. By generating decisions and combining their results, this model improves prediction and reduces the problem of overfitting (Liaw & Wiener, 2002).

Boosting: Boosting is a machine learning technique that uses a set of weak models (usually decision trees) to create a strong model (Freund & Schapire, 1997). In this study, boosting is used to model the relationship between private sector credit and self-employment. The algorithm iteratively adds new models to correct errors in previous models, resulting in more accurate predictions (Friedman, 2001).

K-Means Clustering: K-means clustering is an unsupervised algorithm used to group data into K clusters (MacQueen, 1967). In this study, K-Means can be used for similar patterns in reliable private sector and self-employment data in different provinces. This method can help to identify provincial groups with similar characteristics, which can help to adjust targeted policies (Hartigan & Wong, 1979).

Lasso Regression: Lasso regression is a linear regression technique that uses L1 tuning for feature selection and avoids overfitting (Tibshirani, 1996). In this study, lasso regression is used to identify the most important specific credits that affect self-employment. This method creates a simpler and more interpretable model by eliminating or reducing less important changes (Zou & Hastie, 2005).

Enhanced Hebodian Tree (XGBoost): XGBoost is an optimized implementation of algorithms optimized for speed and efficiency (Chen & Guestrin, 2016). In this study, XGBoost is used to model complex international, private sector, and self-employed relationships. The algorithm uses advanced regularization techniques, parallel processing, and efficient memory management to improve prediction accuracy and reduce computation time (Nielsen, 2016).

Spatial Autoregression (SAR) Model: The Spatial Autoregression (SAR) model is a spatial econometric method used to analyze relationships between variables by considering spatial dependencies (Anselin, 1988). In this study, SAR is used to examine The repercussions of private sector credit on self-employment, taking into account interactions between neighboring provinces. The SAR model includes a spatial autoregression component that models spatial dependence in the dependent variable (LeSage & Pace, 2009).

Spatial Error Model (SEM): The spatial error model (SEM) is another method in spatial econometrics used to model spatial dependence in the error component of the model (Anselin, 2003). In this study, SEM is used to examine the effect of private sector credit on self-employment by accounting for unobservable spatial effects. The SEM model assumes that there is spatial dependence in the error component of the model, that is, shocks or unobservable factors in one province can affect neighboring provinces (Elhorst, 2014).

Spatial Durbin Model (SDM): The spatial Durbin model (SDM) is a more comprehensive model in spatial econometrics that accounts for spatial dependence in both the dependent and independent variables (LeSage & Pace, 2009). In this study, the SDM is used to analyze The repercussions of private sector credit on self-employment by considering more complex interactions between provinces. The model includes both spatial autoregressive components (such as SAR) and spatial lags of the independent variables (Elhorst, 2010).

3.2 Neighborhood matrix

In spatial econometric studies, the Weighting Matrix forms the backbone of spatial models (SAR, SEM, and SDM). This matrix shows how each region

(Iranian provinces) is influenced by its neighboring regions. Therefore, the following describes how the weighting matrix (W) is formed and its role in the three main models (SAR, SEM, and SDM).

How to form the adjacency matrix (W):

To construct the neighborhood matrix W, we first define which regions are considered "neighbors." Common methods are as follows:

- Contiguity method: In this method, if two provinces share a common border, then the number 1 is inserted in row i and column j (or vice versa) of the neighborhood matrix, and 0 otherwise (Anselin, 1988).
- Distance-based method: In this method, weighting is done based on geographical distance (for example, the distance between the centers of the provinces). The inverse of the distance ($1/d_{ij}$) or the inverse of the square of the distance ($1/d_{ij}^2$) or functions such as the exponential function may be used (Anselin, 1988).
- K-nearest neighbors method: In this method, for each province i, the nearest k other provinces are considered neighbors and the rest are set to 0 (Anselin, 1988).

Given the nature of provincial data in Iran, the most common and common method is to use border adjacency. For example, if i and j are two provinces with a common border, the value w_ij = 1 and otherwise it will be 0. Then it is customary to row-standardize this matrix; therefore, the sum of each row will be equal to one and the statistical interpretation of spatial models will be easier. Its general formula will be as follows:

$$W_{ij} = \frac{A_{ij}}{\sum_j A_{ij}} \qquad (5)$$

In other words, for each row i, the row values are divided by the row sum until the sum of the rows is equal to one. The matrix W is of dimensions N×N (the number of provinces or regions) and its diagonal elements (i=i) are usually considered to be zero (i.e., a province cannot be its own neighbor).

i. The Role of the Neighborhood Matrix (W) in the SAR Model

The Spatial Autoregressive Model or SAR is one of the most common spatial econometric models. In this model, spatial dependence is directly incorporated into the dependent variable (here LFPR). The general structure of the model is as follows:

$$LFPR = \alpha + X\beta + \rho\, W\, LFPR + \varepsilon \qquad (6)$$

Where:

- LFPR is the vector of self-employment rates (across all provinces).
- X is a matrix of independent variables (including MGR, TFP, EDUT, OPEN, CI and other explanatory variables).
- β is the vector of coefficients.
- ρ is the Spatial Autoregressive Coefficient, which indicates how much the average effect of self-employment in neighboring provinces on province i is.
- W is the N×N neighborhood matrix.

- ε is the error term.

In this model, the term ρ W LFPR indicates that the self-employment rate of province i is affected by the self-employment rate in neighboring provinces through the coefficient ρ, and the weight of this proximity is determined by the matrix W (LeSage & Pace, 2009).

ii. The role of the neighborhood matrix (W) in the SEM model

The spatial error model or SEM is another type of spatial econometric model in which spatial dependence appears in the error term. The general form of the model is as follows:

$$LFPR = \alpha + X\beta + \xi \tag{7}$$

$$\xi = \lambda W \xi + \upsilon \tag{8}$$

where:

- ξ is the spatial error term and itself follows the spatial autoregressive process.
- λ is the spatial error coefficient that shows how shocks or unobservable factors (discontinuities, omitted variables, etc.) in one province spread to other provinces through proximity.
- W is the adjacency matrix that describes the weights or spatial structure.
- υ is the white noise term.

In this model, instead of the dependent variable itself being directly affected by the dependent variable in its neighbors, the noise (shocks or disturbances) are spread between regions in space. Therefore, W shows its role in the spread of errors from one region to another (Elhorst, 2014).

ii. The role of the adjacency matrix (W) in the SDM model

The Spatial Durbin Model or SDM is more comprehensive than the previous two models and simultaneously considers the existence of spatial dependence in the dependent variable and the independent variables. Its general form is as follows:

$$LFPR = \alpha + X\beta + \rho\, W\, LFPR + W\, X\, \theta + \varepsilon \tag{9}$$

Where:

- ρ represents the spatial autoregression coefficient in the dependent variable.
- W LFPR is the effect of the self-employment rate in the neighbors on province i.
- θ is the vector of coefficients of spatial effects of the independent variables.
- W X is the vector (or matrix) of independent variables in neighboring provinces.
- W is the same neighborhood matrix as defined above.
- ε is the error term.

Therefore, in the SDM model, in addition to the dependent variable in the neighbors (W LFPR), the explanatory variables of the neighbors (W X) can also affect the LFPR of province i. This allows for good consideration of inter-regional interactions at the level of the dependent variable and the independent variables (Fingleton & Le Gallo, 2008).

3.3 Combination of AI and spatial econometrics

In order to comprehensively and accurately analyse The repercussions of private sector credit on the self-employment rate in Iran, the present study used a combination of two approaches, artificial intelligence and spatial econometrics. The reasons and methodology for this combination are as follows:

Reasons for using the combination of artificial intelligence and spatial econometrics

1- Identification of non-linear and complex relationships: Artificial intelligence models, especially deep neural networks such as MLP, CNN, RNN and other machine learning techniques, have a high ability to identify non-linear and complex relationships between variables. This capability allows research to identify complex patterns and interactions between private sector credit and the self-employment rate that may not be identified by traditional linear models (Abiodun et al, 2018).
2- Identification and analysis of spatial dependencies: Spatial econometrics, including SAR, SEM and SDM models, are used to identify and model spatial dependencies between different regions. In the context of the present study, different provinces of Iran are considered as analytical units and these models help to identify threshold effects and spatial interactions between these provinces (Nikpey et al, 2024).
3- Combining the benefits of both approaches: By combining AI and spatial econometrics, research can benefit from both the power of AI models in recognising complex patterns and making accurate predictions, and the ability of spatial econometric models in controlling spatial dependencies and providing local economic analysis. This combination leads to more accurate and comprehensive results (Ansari & Binninger, 2022).

4.3 Combining Artificial Intelligence with Spatial Econometrics

In the present study, artificial intelligence was combined with spatial econometrics to analyse The repercussions of private sector credit on self-employment rate in Iran in the form of a hybrid model. The final model is defined as follows:

$$LFPR_{it} = \mathrm{NN}(\beta_0 + \beta_1 \mathrm{MGR_{it}} + \beta_2 \mathrm{TFP_{it}} + \beta_3 \mathrm{EDUT_{it}} + \beta_4 \mathrm{OPEN_{it}} + \beta_5 \mathrm{CI_{it}})\rho \sum_{j=1}^{n} \mathrm{w_{ij}} + \mathrm{LFPR_{it}} + \phi_{\mathrm{it}} \quad (10)$$

5.3 Combining Artificial Intelligence with Spatial Econometrics

In this model, the NN(0) component represents the artificial intelligence (AI) model, which can be a Multilayer Perceptron (MLP) or any other AI model. This section is responsible for modeling the nonlinear relationships among the independent variables, including the Microcredit to GDP ratio (MGRi,t), Total

Factor Productivity (TFPi,t) Education Expenditure (EDUTi,t), Economic Openness Index (OPENi,t), and Capital Formation Rate (CIi,t). The AI model is trained to identify complex and nonlinear patterns and to predict the effects of these variables on the self-employment rate (LFPRi,t).

The second part of the model incorporates the spatial econometrics component, represented as:

$$\rho j{=}1nwij{+}LFPRit \tag{11}$$

In this section, ρis the spatial correlation index and w_{ij} are the elements of the spatial weight matrix (W) that represent the spatial relationships between provinces. This component allows the model to take into account the influence of the self-employment rate of neighboring provinces on the province under study, so that spatial dependencies are controlled in the analysis.

$$\phi it \tag{12}$$

The error term (ϕi,t) constitutes the final part of the model, encompassing random factors and unexplained variances. The process of combining the models proceeds as follows: first, data related to self-employment rates, the Microcredit to GDP ratio, and control variables are collected and processed. Then, using the spatial weight matrix (W), spatial dependencies among provinces are identified. The AI model is trained using these variables, and its output is incorporated as the primary economic function into the spatial econometrics model. Finally, by optimizing the hybrid model through techniques such as hyperparameter tuning and cross-validation, the prediction accuracy and generalizability of the model are enhanced. This hybrid approach facilitates a more precise and comprehensive analysis of The repercussions of private sector credit on self-employment rates.

The integration of artificial intelligence with spatial econometrics in this study provides a robust framework for analysing The repercussions of private sector credit on self-employment rates. By leveraging the strengths of AI in capturing complex, non-linear relationships and the ability of spatial econometrics to account for spatial dependencies, the hybrid model achieves more accurate and comprehensive results. This approach provides valuable insights for economic policymakers seeking to understand and promote self-employment through targeted credit interventions.

4. Empirical Results

This section examines the descriptive statistics of the research variables. It should be noted that the Winsorize method was used to reduce The repercussions of outliers and abnormal data on the analysis results. The Winsorize method, named in honor of Charles Winsor, is a statistical transformation that limits extremely high or low values in the data. This reduces The repercussions of invalid outliers and allows for more accurate and reliable statistical analysis. Using this method allows us to obtain a more accurate picture of the statistical properties of the variables by reducing the deviations caused by abnormal data. On the flip side, to homogenize the data, or in other words, to unify the nature of the research data, min-max scaling (min-max scaling, also known as min-max normalization, is a method for standardizing data in the range [0, 1]. This method, by preserving the main relationships between the data, transforms them into a common scale, which is very useful for comparing and analyzing variables with different units (Jain et al., 2005) has been used. Therefore, Table 1 shows the status of the research variables in terms of descriptive statistics indicators:

Table 1. Descriptive statistics

ROW	Varible	Min	Max	Mean	Median	Skewness	Shapiro Wilk	P.Value
1	LFPR	0	1	0/46702	0/46588	0/06529	0/99837	0/47646
2	MGR	0	1	0/47999	0/48192	-0/01052	0/99861	0/63161
3	TFP	0	1	0/45113	0/44627	0/04502	0/99855	0/58892
4	EDUT	0	1	0/51792	0/51808	-0/07140	0/99861	0/66607
5	OPEN	0	1	0/47167	0/47157	0/02782	0/99835	0/46271
6	CI	0	1	0/47244	0/47162	-0/02305	0/99884	0/78472

Source: *Research Findings*

The descriptive statistics presented in Table 1 show that the labour force participation rate (LFPR), with a mean of 0.46702 and a median of 0.46588, indicates that about 47% of the population participates in the labour force. The low positive skewness (0.06529) indicates an almost symmetrical distribution of this variable. The Shapiro-Wilk test (0.99837) and the p-value (0.47646) indicate that the distribution of the LFPR does not deviate significantly from normality. The money growth ratio (MGR), with a mean of 0.47999 and a median of 0.48192, indicates moderate money growth. The very low negative skewness (-0.01052) and the Shapiro-Wilk test also confirm the normality of the distribution of this variable. Other variables such as Total Factor Productivity (TFP), Education Expenditure (EDUT), Economic Openness Index (OPEN) and Capital Accumulation Rate (CI) also show similar patterns. Closely spaced means and medians, low skewness (positive or negative) and Shapiro-Wilk tests with p-values above 0.05 all point to a normal distribution of these variables. For example, education expenditure (EDUT) with a mean of 0.51792 indicates that more than half of the resources are allocated to education, while the economic openness index (OPEN) with a mean of 0.47167 indicates a moderate degree of economic openness. Overall, the descriptive statistics show that all the variables studied have a relatively normal and symmetric distribution, which is suitable for subsequent statistical analyses. These features highlight the importance of using appropriate spatial econometric techniques. Understanding these patterns is crucial for formulating policies that can influence labour force participation, economic growth and other key variables.

Tabel 2. Unit root test

Varible	Levin, Lin & Chu	Im, Pesaran	ADF	PP	Obs

	Statistic	prob	Statistic	prob	Statistic	prob	Statistic	prob	
LFPR	-6/0974	0/0000	-6/157	0/0000	104/445	0/0000	104/284	0/0000	1054
MGR	-7/0544	0/0000	-8/1229	0/0000	152/479	0/0000	150/338	0/0000	1054
TFP	-3/3402	0/0004	-4/0944	0/0000	72/9023	0/0003	75/6672	0/0001	1054
EDUT	-3/1765	0/0007	-3/4140	0/0003	62/1607	0/0043	62/2307	0/0043	1054
OPEN	-6/4569	0/0000	-6/7041	0/0000	112/428	0/0000	109/318	0/0000	1054
CI	1/37068	0/0027	-0/2417	0/0045	36/7280	0/0000	39/9645	0/0000	1054

Source: *Research Findings*

Unit root tests confirm all variables are stationary, satisfying a key econometric requirement. This conclusion is supported by four tests (Levin, Lin & Chu; Im, Pesaran; ADF; and PP), all showing p-values < 0.05, rejecting the null hypothesis of a unit root. LFPR, MGR, and OPEN exhibit particularly strong stationarity, indicated by large test statistics and small p-values (e.g., LFPR and MGR have Levin, Lin & Chu statistics of -6.0974 and -7.0544, respectively, both with p-values of 0.0000). TFP and EDUT are also stationary, though with slightly smaller test statistics. While CI has a positive Levin, Lin & Chu statistic (1.37068), the other three tests confirm its stationarity. The overall stationarity of all variables at level avoids differencing, preserving data integrity and allowing direct interpretation of regression coefficients.

Table 3. Spatial econometric diagnostic tests

Test	Statistic	p-value	Alternative Hypothesis
Hausman Test	4.5854	0.5981	One model is inconsistent
LM Test for Spatial Dependence	32.269	1.343e-08	Spatial lag dependence
Moran's I Test for All Residuals	36.032	< 2.2e-16	Greater

Source: *Research Findings*

The results of the spatial econometric diagnostic tests in Table 3 provide important information. The Hausman test, with a statistic of 4.5854 and a p-value of 0.5981, shows that there is no significant difference between the fixed effects model and the random effects model, so the use of the random effects model is appropriate. The LM test for spatial dependence with a statistic of 32.269 and a very small p-value (1.343e-08) strongly suggests the presence of spatial dependence in the data, indicating the need to use spatial models. The Moran's I test on all residuals with a statistic of 36.032 and a p-value of less than 2.2e-16 also strongly confirms the presence of spatial autocorrelation in the residuals. Taken together, these results show the importance of taking into account the spatial structure of the data and suggest that the use of spatial econometric models is necessary for a more accurate and reliable analysis of the data.

Table 4. Investigating the Effect of Microcredit on Self-Employment in Iran Using SEM

Row	Varible	Estimaet	Std.Error	Z-value	P-Value
1	MGR	-1.16807	0.0376	-31.037	0.0000
2	TFP	3.54197	0.3751	9.4415	0.0000
3	EDUT	1.80173	0.0732	24.590	0.0000
4	OPEN	-5.06348	0.7689	-6.8549	0.0000
5	CI	-0.77167	0.0221	-34.794	0.0000
6	λ			0.97649	
7	Asymptotic Standard Error			0.0095601	
		Statistic		P-value	
8	LR test	468.08		0.0000	
	Z test	102.14		0.0000	
	Wald test	10433		0.0000	
9	Log Likelihood			-799.4277	
10	AIC			1614.9	
11	AIC for lm			2080.9	

Source: *Research Findings*

Table 4 reveals a significant negative relationship between the microcredit to GDP ratio (MGR) and the labor force participation rate (LFPR) in Iran. The estimated MGR coefficient is -1.16807 (p-value = 0.0000), suggesting that increased microcredit corresponds to decreased self-employment. This could be due to several factors: First, the ineffective distribution of microcredit prevents it from reaching small entrepreneurs who need capital. Bureaucracy, lack of information, and potential corruption hinder access. Second, microcredit may be misused for unproductive expenses or debt repayment, rather than business investment. Finally, increased microcredit can benefit larger firms, enabling them to expand and create formal jobs, attracting individuals away from self-employment. This shift towards formal employment contributes to the overall decline in self-employment rates.

Conversely, total factor productivity (TFP) positively and significantly affects self-employment (coefficient = 3.54197, p-value = 0.0000). Higher productivity leads to increased self-employment opportunities. Similarly, educational expenditure (EDUT) shows a positive impact (coefficient = 1.80173, p-value = 0.0000), highlighting the importance of education for self-employment.

However, the economic openness index (OPEN) and the capital formation rate (CI) negatively affect self-employment (coefficients of -5.06348 and -0.77167, respectively, both significant at p-value = 0.0000). Increased foreign competition and investment in capital-intensive sectors may reduce self-employment prospects.

The structural equation model (SEM) demonstrates a good fit (λ = 0.97649, standard error = 0.0095601). LR, Z, and Wald tests (p-value = 0.0000) confirm the significance of the model variables. The lower AIC value of the SEM (1614.9) compared to ordinary linear regression (2080.9) further supports its superior fit.

These findings suggest policymakers should focus on enhancing productivity, investing in education, and addressing challenges in credit markets to promote self-employment.

Table 5. Investigating the Effect of Microcredit on Self-Employment in Iran Using SAR

Row	Varible	Estimaet	Std.Error	Z-value	P-Value
1	MGR	-1.3487	0.01862	-72.432	0.0000
2	TFP	3.4372	0.17817	22.134	0.0000
3	EDUT	1.9211	0.03520	54.577	0.0000
4	OPEN	-4.8860	0.37631	-12.984	0.0000
5	CI	-0.8954	0.01119	-80.020	0.0000
6	ρ			0.88074	
7	Asymptotic Standard Error			0.0076776	
		Statistic		P-value	
8	LR test	1138		0.0000	
	Z test	114.72		0.0000	
	Wald test	13160		0.0000	
	LM test	3.5226		0.0605	
9	Log Likelihood			-464.4685	
10	AIC			944.94	
11	AIC for lm			2080.9	

Source: *Research Findings*

Table 5 shows a significant negative relationship between microcredit (MGR) and self-employment (LFPR) in Iran (coefficient = -1.3487, p-value = 0.0000). Increased microcredit corresponds with decreased self-employment, suggesting potential inefficiencies in microcredit utilization or barriers to its use for self-employment ventures. TFP and education expenditure (EDUT) positively affect self-employment (coefficients of 3.4372 and 1.9211, respectively, both significant). Conversely, economic openness (OPEN) and capital formation (CI) negatively impact self-employment. The high spatial correlation coefficient (ρ = 0.88074) confirms strong regional interdependencies in self-employment rates. The spatial autoregressive (SAR) model provides a better fit than a simple linear model (AIC reduced from 2080.9 to 944.94). These findings highlight the need for revised microcredit policies and a focus on productivity, education, and economic structures to effectively promote self-employment in Iran.

Table 6. Investigating the Effect of Microcredit on Self-Employment in Iran Using SDM

Row	Varible	Estimaet	Std.Error	Z-value	P-Value
1	MGR	-1.50285	0.00268	-559.68	0.0000
2	TFP	4.00994	0.02338	171.50	0.0000
3	EDUT	2.00439	0.00460	434.80	0.0000
4	OPEN	-5.05321	0.04912	-102.29	0.0000
5	CI	-1.00114	0.00163	-610.59	0.0000
6	lag.MGR	-1.52355	0.01162	-131.08	0.0000
7	lag.TFP	3.09755	0.07398	41.056	0.0000

8	lag.EDUT	1.01559	0.01718	59.115	0.0000
9	lag.OPEN	1.77363	0.13777	12.874	0.0000
10	lag.CI	-1.00670	0.00756	-133.11	0.0000
11	ρ			0.496	
12	Asymptotic Standard Error			0.0031804	
		Statistic		P-value	
	LR test	1633.8		0.0000	
13	Z test	155.96		0.0000	
	Wald test	24322		0.0000	
	LM test	0.3686		0.54374	
14	Log Likelihood			381.3011	
15	AIC			-736.6	
16	AIC for lm			895.17	

Source: *Research Findings*

Table 6's Spatial Durbin Model (SDM) results reveal a negative and significant relationship between microcredit (MGR) and self-employment (LFPR) in Iran (coefficient = -1.50285, p-value = 0.0000). Increased microcredit in a region and its neighbors (spatial lag coefficient = -1.52355, also significant) decreases regional self-employment, questioning microcredit policy effectiveness. Conversely, TFP exhibits a positive and significant impact, both regionally and spatially (coefficients = 4.00994 and 3.09755, respectively). Similarly, education expenditure (EDUT) shows positive regional and spatial effects (coefficients = 2.00439 and 1.01559). Economic openness (OPEN) negatively affects local self-employment but positively influences neighboring regions (coefficients = -5.05321 and 1.77363). Capital formation (CI) displays negative regional and spatial effects. A significant spatial autocorrelation (ρ = 0.496) confirms regional interdependencies in self-employment. The SDM's superior fit (AIC decreasing from 895.17 in the linear model to -736.6) highlights the importance of spatial factors. Policy recommendations include reviewing microcredit strategies and focusing on productivity, education, and economic structures, while considering spatial dynamics, to boost self-employment.

Table 7. Examining the normality of the residuals of spatial models

Test	Data	W Statistic	p-value
Shapiro-Wilk Normality Test for Spatial Error Model	residuals(sem_model)	0.99683	0.6407
Shapiro-Wilk Normality Test for Spatial Durbin Model	residuals(sdm_model)	0.99683	0.6421
Shapiro-Wilk Normality Test for spatial autoregressive vector models.	residuals(SAR_model)	0.9964	0.02131

Source: *Research Findings*

The results of the normality test of the residuals of the spatial models are presented in Table 7. For all three models (spatial error model, spatial Durbin model, and spatial autoregressive vector models), the Shapiro-Wilk test was performed. The W statistic for the spatial error model and the spatial Durbin model is the same and equal to 0.99683, with p values of 0.6407 and 0.6421, respectively. For the spatial fixed effects model, the W statistic is equal to 0.9964 and the p value is equal to 0.02131. In all cases, the p values are greater than the significance level of 0.05, indicating that the null hypothesis of normality of the residuals is not rejected. These results indicate that the residuals of all three spatial models have a normal distribution, which is one of the important assumptions in statistical analyses. These findings confirm the validity of the spatial models used and indicate that the results obtained from these models are reliable.

Table 8. Investigating the Effect of Microcredit on Self-Employment in Iran Using Artificial intelligence

MODEL	R2	MAE	MAPE	RMSE	MSE	MedAE	MBE
MLP	0.469	0.568	272	0.706	0.499	0.473	0.0676
CNN	0.525	0.532	240	0.655	0.429	0.758	0.0504
RNN	0.511	0.522	221	0.663	0.440	0.399	0.0261
LSTM	0.492	0.517	206	0.676	0.457	0.412	0.0576
GRU	0.474	0.561	237	0.696	0.485	0.487	0.0659
GNN	0.523	0.519	228	0.662	0.439	0.423	0.0680
DBN	0.509	0.537	207	0.669	0.447	0.458	0.0724
PCA	0.513	0.515	204	0.665	0.429	0.435	0.0520
ANN	0.522	0.514	236	0.667	0.446	0.434	0.0679
TNN	0.484	0.544	241	0.689	0.474	0.454	0.0095
SVR	0.514	0.503	185	0.637	0.406	0.442	0.0612
Decision-Tree	0.460	0.538	199	0.669	0.447	0.449	0.0642
Random- Forest	0.530	0.495	184	0.620	0.384	0.422	0.0698
Gradient-Bossting	0.521	0.522	122	0.654	0.428	0.472	0.0530
KNN	0.471	0.523	178	0.654	0.428	0.450	0.0530
Laso-Regression	0.573	0.471	193	0.595	0.354	0.399	0.0487
Ridge-Regression	0.569	0.475	192	0.597	0.356	0.403	0.0569
XGBoost	0.473	0.535	186	0.680	0.463	0.416	0.0738

Source: *Research Findings*

Analysis of AI models investigating microcredit's impact on Iranian self-employment (Table 8) reveals Lasso regression's superior performance. Achieving an R^2 of 0.573, it explained 57.3% of self-employment rate (LFPR) variance, outperforming other models including Ridge Regression (R^2=0.569), Random Forest (R^2=0.530), and CNN (R^2=0.525). Lasso also minimized error metrics, boasting the lowest MAE (0.471), RMSE (0.595), and MAPE (193).

These findings suggest regression models, particularly Lasso and Ridge, effectively analyze this relationship due to their ability to handle multicollinearity and feature selection. The results confirm microcredit's significant influence on self-employment, effectively modeled by regression techniques. This offers valuable insights for policymakers and researchers, demonstrating the power of AI in understanding microcredit's impact across Iranian provinces.

Further research (Table 6) reveals a complex relationship between private sector credit and self-employment. While microcredit alone may decrease self-employment, its positive impact emerges when combined with factors like total factor productivity (TFP), educational expenditures (EDUT), and inter-provincial spatial dependencies. Therefore, effective self-employment growth requires integrated policies addressing private sector credit alongside investments in education, productivity enhancements, and regional spatial interactions.

Table 9. Investigating The repercussions of microcredit on self-employment in Iran using a combination of artificial intelligence and spatial models

MODEL	R2	MAE	MAPE	RMSE	MSE	MedAE	MBE
MLP	98.0	0.1111	67.8	0.138	0.019	0.101	0.024
CNN	98.1	0.1080	79.5	0.133	0.018	0.096	0.018
RNN	98.1	0.1077	65.1	0.134	0.018	0.084	0.029
LSTM	98.4	0.1079	71.7	0.136	0.019	0.091	0.025
GRU	98.0	0.1151	75.8	0.142	0.019	0.101	0.025
GNN	96.8	0.1187	77.0	0.174	0.031	0.093	0.023
DBN	98.3	0.1055	69.2	0.134	0.018	0.085	0.014
PCA	98.2	0.1089	91.2	0.132	0.017	0.092	0.025
ANN	98.1	0.1093	59.4	0.132	0.017	0.101	0.022
TNN	98.4	0.1081	63.2	0.132	0.018	0.096	0.023
SVR	97.4	0.1215	81.0	0.161	0.026	0.102	0.028
Decision-Tree	94.3	0.1883	103	0.236	0.056	0.160	0.027
Random- Forest	98.1	0.1118	71.7	0.136	0.019	0.099	0.026
Gradient-Bossting	97.4	0.1716	79.9	0.211	0.045	0.149	0.023
KNN	94.3	0.1886	92.3	0.239	0.057	0.167	0.013
Laso-Regression	98.0	0.0936	68.6	0.113	0.013	0.084	0.021
Ridge-Regression	98.1	0.0943	65.1	0.114	0.013	0.083	0.022
XGBoost	97.9	0.1180	70.2	0.142	0.023	0.106	0.027

Varible	SEM		SAR		SDM	
	Estimaet	Z-value	Estimaet	Z-value	Estimaet	Z-value
MGR	-1.16807	-31.037	-1.3487	-72.432	-1.50285	-559.68
TFP	3.54197	9.4415	3.4372	22.134	4.00994	171.50
EDUT	1.80173	24.590	1.9211	54.577	2.00439	434.80
OPEN	-5.06348	-6.8549	-4.8860	-12.984	-5.05321	-102.29
CI	-0.77167	-34.794	-0.8954	-80.020	-1.00114	-610.59

Source: *Research Findings*

An integrated approach of artificial intelligence and spatial econometrics was employed to investigate microcredit's effect on self-employment in Iran, focusing on variables such as the microcredit-to-GDP ratio (MGR), total factor productivity (TFP), education expenditure (EDUT), openness (OPEN), and capital formation rate (CI) alongside the self-employment rate (LFPR). Overall, all tested models performed satisfactorily. Among the AI models, LSTM and TNN achieved the highest explanatory power, with an R^2 of 98.4%, closely followed by DBN (98.3%), PCA (98.2%), and then CNN, RNN, ANN, and Ridge Regression (each at 98.1%). Even the lower-ranking Decision-Tree and KNN models demonstrated an acceptable predictive capacity, both exceeding 94% for R^2. Beyond the coefficient of determination, errors were also considered. Laso

Regression scored the smallest mean absolute error (MAE) of 0.0936, reflecting high predictive precision, with Ridge Regression and DBN showing similarly favorable MAE values (0.0943 and 0.1055, respectively). In terms of root mean square error (RMSE), Laso and Ridge produced the lowest figures (0.113 and 0.114), while Decision-Tree and KNN exhibited higher quantitative errors despite strong R^2 values. Spatial SEM, SAR, and SDM models revealed a significant spatial autocorrelation coefficient (ρ), indicating that self-employment rates in one region are influenced by neighboring areas. Notably, MGR, OPEN, and CI displayed consistently negative coefficients, suggesting that inefficiencies in credit allocation, foreign competition, and capital-intensive investments may dampen self-employment. Conversely, TFP and EDUT were positively and significantly linked to self-employment, underscoring the role of technological improvements, skill development, and educational investment. Overall, while microfinance can assist self-employment, it cannot operate in isolation; supportive conditions such as a stable business environment and comprehensive policy measures are essential. LSTM, TNN, DBN, and Ridge Regression, given their strong R^2 and lower error metrics, emerge as particularly effective models for forecasting self-employment rates.

5. Concluding Remarks

This study investigates the repercussions of private sector credit on self-employment in Iran through a hybrid approach that combines artificial intelligence and spatial econometric models. The panel data analysis covering the period from 1990 to 2023 reveals a complex relationship between private sector credit and the self-employment rate in Iran. Contrary to initial expectations, the findings indicate a negative and significant effect of the microcredit-to-GDP ratio (MGR) on the labor force participation rate (LFPR), which serves as an indicator of self-employment. This negative relationship was consistent across all models employed, including both artificial neural network and spatial econometric models.

Several factors contribute to this negative association between microcredit and self-employment in Iran. A primary reason is the ineffective utilization of these funds for sustainable employment creation. Often, individuals resort to using loans to pay off existing debts or purchase consumer goods, leading to financial resources being allocated to unproductive activities rather than generating new job opportunities. Additionally, the manner in which banks and financial institutions in Iran disburse microcredits often in small amounts due to risk concerns and uncertainties regarding repayment further hinders the potential for these loans to support self-employment.

Another critical factor is the lack of support services beyond mere loan repayment. Accessing financial resources without adequate training in business management, marketing, accounting, and other entrepreneurial skills can lead to the failure of many self-employment ventures. Borrowers often struggle to optimize the use of the funds they receive due to insufficient knowledge and experience, resulting in significant challenges for their businesses. Therefore, providing training and advisory services alongside microfinance is crucial for the success of self-employment initiatives.

Moreover, a lack of coordination among various institutions involved in self-employment support exacerbates the negative impact of microcredit on job creation. The support policies from different agencies, such as the Ministry of Labor, the Ministry of Industry, and the Central Bank, often lack alignment, creating confusion for applicants and diminishing the effectiveness of employment programs. For instance, while policymakers advocate for self-employment promotion, banks may hesitate to extend microcredit due to risk or profitability concerns. Thus, enhancing coordination among institutions and developing coherent support policies is essential to maximize the positive effects of microcredit on self-employment.

The results from the spatial econometric models indicate significant spatial dependence in the self-employment rates across different regions of Iran. The spatial autocorrelation coefficient (ρ) was significant in all spatial autoregression (SAR), spatial error (SEM), and spatial Durbin (SDM) models, suggesting that the self-employment rate in one region is influenced by the rates in neighboring regions, in addition to other control variables. This finding underscores the importance of considering spatial spillovers in employment and entrepreneurship policies.

Among the independent variables in the spatial models, the coefficients for the microcredit-to-GDP ratio (MGR), openness index (OPEN), and capital formation rate (CI) were negative and significant across all three models. Specifically, increases in these variables were associated with a decline in the self-employment rate in the regions. While this outcome may initially seem surprising, it can be explained. In the case of microcredit, the negative coefficient reflects inefficiencies in the allocation and direction of loans toward sustainable job creation.

Moreover, greater economic openness often leads to increased imports and foreign competition, which can pressure small businesses and self-employment opportunities. Similarly, a higher capital formation rate may indicate investments in larger, capital-intensive sectors that do not necessarily foster self-employment opportunities. Conversely, the positive and significant coefficients for total factor productivity (TFP) and education expenditure (EDUT) in the spatial models highlight the importance of these factors in promoting self-employment. Enhancing productivity through improved technology, labor skills, and production processes lays the groundwork for small business creation and increased self-employment. Additionally, investments in education and skills development empower individuals to enter the labor market and generate job opportunities for themselves.

The combined results from the artificial intelligence models and spatial econometrics corroborate the research findings. The Long Short-Term Memory (LSTM) and Transformer Neural Network (TNN) models demonstrated the highest accuracy among the models analyzed, achieving a coefficient of determination of 98.4%. This indicates that these models can explain 98.4% of the variation in the self-employment rate. Following closely were the Deep Belief Network (DBN) models at 98.3%, and Principal Component Analysis (PCA) at 98.2%. Even models such as Decision Tree and K-Nearest Neighbors (KNN), which performed less effectively than others, still managed to predict the self-employment rate with a coefficient of determination of 94.3%.

In addition to the coefficient of determination, other performance metrics are important. For instance, the Lasso regression model exhibited the lowest mean absolute error (MAE) at 0.0936, indicating high accuracy in predicting values close to reality. The Ridge and DBN regression models also performed well, with MAEs of 0.0943 and 0.1055, respectively. In terms of root mean square error (RMSE), the Lasso and Ridge regression models had the lowest errors in predicting self-employment rates, with values of 0.113 and 0.114.

Comparing the results of this study with previous research reveals both consistencies and discrepancies. For instance, the finding of a negative effect of microcredit on self-employment aligns with the work of Kananurak & Sirisankanan (2020), yet contrasts with studies by Tayyibi & Abbasloo (2009) and Saeedi (2012), which indicated a positive effect of bank facilities on employment. These differences may stem from variations in the time periods studied, analytical methods.

Author Contributions

Conceptualization, R. Taheri Haftasiabi; methodology, R. Taheri Haftasiabi and A. Naderi; validation, R. Taheri Haftasiabi; formal analysis, R. Taheri Haftasiabi, Y. mohammadzade, A. Naderi; resources, A. Zavari Rezai; writing—original draft preparation, R. Taheri Haftasiabi; A. Zavari Rezai; writing—review and editing, all authors; All authors have read and agreed to the published version of the manuscript.

Funding

This research received no external funding.

Conflicts of Interest:

The authors declare no conflict of interest.

Data Availability Statement

The data used in this study are available from 1990 to 2023 on the websites (https://www.rug.nl/ggdc/productivity/pwt/,https://data.worldbank.org/indicator/SE.XPD.TOTL.GD.ZS?locations=IR , https://www.cbi.ir/page/20949.aspx).

References

Abbas , J, Lorente, D, Amjid , M, Al-Sulaiti, K, Al-Sulaiti, I, & Aldereai, O. (2024). Financial innovation and digitalization promote business growth: The interplay of green technology innovation, product market competition and firm performance. *Innovation and Green Development*, 3(1), 100-111. doi:10.1016/j.igd.2023.100111.

Abdulraqeb, H, & Shahin, W. (2024). The Impact of Financial Resources Availability on Self-Employment Rates in Saudi Arabia. In Achieving Sustainable Business Through Artificial Intelligence, Technology Education and Computer Science. 159, 537-549. https://doi.org/10.1007/978-3-031-48519-8_38

Abiodun, O. I., Jantan, A., Omolara, A. E., Dada, K. V., Mohamed, N. A., & Arshad, H. (2018). State-of-the-art in artificial neural network applications: A survey. Heliyon, 4(11), e00938. https://doi.org/10.1016/j.heliyon.2018.e00938

Abiola, B, isola, L, Asaleye, A, & Okafor, T. (2020). Financial stability and entrepreneurship development in sub-Sahara Africa: Implications for sustainable development goals. Cogent Social Sciences, 6 (1), 1798330. doi:10.1080/23311886.2020.1798330

Acs, Z. J, & Szerb, L. (2007). Entrepreneurship, economic growth and public policy. Small business economics, 28(2), 109-122. doi:10.1007/s11187-006-9012-3.

Alfaro, L, Chanda, A, Kalemli-Ozcan, S, & Sayek, S. (2003). FDI and Economic Growth: The Role of Local Financial Markets. SSRN Electronic Journal, 64(1), 89-112. doi:10.1016/S0022-1996(03)00081-3

Amini Milani, Minoo, Alipour, Mohammadsadegh, & Mahmoodzadeh, Alireza. (2021). Evaluation of Employment Policies in Iran. JOURNAL OF ECONOMIC STUDIES AND POLICIES, 8(1 (15), 79-106. (in Persian).https://sid.ir/paper/956888/en

Amini, A. (2015). Analysis of the labor market and employment generation policies of the Iranian economy with emphasis on the Fourth Economic, Social and Cultural Development Plan. J. Economic Magazine, 5(6), 23-40. (in persian). http://ejip.ir/article-۶۳۱-۱-fa.html.

Ansari, O. B., & Binninger, F.-M. (2022). A deep learning approach for estimation of price determinants. International Journal of Information Management Data Insights, 2(2), 100101. https://doi.org/10.1016/j.jjimei.2022.100101

Anselin, L. (1988). Spatial econometrics: Methods and models. Kluwer Academic Publishers. https://link.springer.com/book/10.1007/978-94-015-7799-1

Anselin, L. (2003). Spatial externalities, spatial multipliers, and spatial econometrics. International Regional Science Review, 26(2), 153-166. https://journals.sagepub.com/doi/10.1177/0160017602250972 (text/html)

Arestis, P, & Demetriades, P. (1997). Financial Development and Economic Growth: Assessing the Evidence. The Economic Journal, 107(442), 783-799. doi:org/10.1111/j.1468-0297.1997.tb00043.x

Ata-Agboni, J, Adama, I, Sumaila, A, & Suleiman, R. (2024). Assessment of the Causes of Poverty and Unemployment in Omala Local Government Area, Kogi State, Nigeria. International Journal of Democracy and Development Studies, 6(4), 34-42. journals.rcmss.com/index.php/ijdds/article/view/968

Augsburg, B, De Haas, R, Harmgart, H, & Meghir, C. (2015). The impacts of microcredit: Evidence from Bosnia and Herzegovina. American Economic Journal: Applied Economics, 7(1), 183-203. DOI: 10.1257/app.20130272

Bahdanau, D, Cho, K, & Bengio, Y. (2015). Neural machine translation by jointly learning to align and translate. https://arxiv.org/abs/1409.0473.

Banerjee, A, Karlan, D, & Zinman, J. (2015). Six randomized evaluations of microcredit: Introduction and further steps. American Economic Journal: Applied Economics, 7(1), 1-21. http://dx.doi.org/10.1257/app.20140287

Barba-Sánchez, V, & Atienza-Sahuquillo, C. (2017). Entrepreneurial motivation and self-employment: evidence from expectancy theory. Int Entrep Manag J, 13, 1097-1115. doi:10.1007/s11365-017-0441-z

Barro, R. J. (1991). Economic growth in a cross section of countries. The Quarterly Journal of Economics, 106(2), 407-443. http://hdl.handle.net/10.2307/2937943

Beaugrand, P. (2004). And Schumpeter Said, “This Is How Thou Shalt Grow”: The Further Quest for Economic Growth in Poor Countries. IMF Working Paper, 1-22. https://www.imf.org/external/pubs/ft/wp/2004/wp0440.pdf

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

Becker, G. S. (1993). Human capital: A theoretical and empirical analysis, with special reference to education. University of Chicago Press. https://econpapers.repec.org/bookchap/nbrnberbk/beck94-1.htm

Bengio, Y, Lamblin, P, Popovici, D, & Larochelle, H. (2007). Greedy layer-wise training of deep networks. Advances in Neural Information Processing Systems, 19, 153-160. https://www.researchgate.net/publication/200744514_Greedy_layer-wise_training_of_deep_networks

Blau, F, & Kahn, L. (1999). Chapter 25 - Institutions and Laws in the Labor Market. Handbook of Labor Economics, 3(A), 1399-1461. doi:10.1016/S1573-4463(99)03006-0

Boldureanu, G, Ionescu, A. M, Bercu, A. -M, Bedrule-Grigoruță, M. V, & Boldureanu, D. (2020). Entrepreneurship Education through Successful Entrepreneurial Models in Higher Education Institutions. Sustainability, 12(3), 12-67. doi:10.1016/j.jik.2023.100353

Breiman, L, Friedman, J, Stone, C. J, & Olshen, R. A. (1984). Classification and regression trees. CRC press. https://doi.org/10.1201/9781315139470

Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5-32.
Caraher, K, & Reuter, E. (2019). Vulnerability of the 'entrepreneurial self': Analysing the interplay between labour markets and social policy. Journal of Social Policy, 27(2), 199-217. https://doi.org/10.1332/175982718X15451303785398
Central Bank of the Islamic Republic of Iran. (2021). Selected Economic Statistics. Available at: https://www.cbi.ir/page/20949.aspx
Chen, T, & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 785-794. https://dl.acm.org/doi/10.1145/2939672.2939785.
Cho, K, Van Merriënboer, B, Gulcehre, C, Bahdanau, D, Bougares, F, Schwenk, H, & Bengio, Y. (2014). Learning phrase representations using RNN encoder-decoder for statistical machine translation. https://arxiv.org/abs/1406.1078.
Cho, Y, Robalino, D, & Watson, S. (2016). Supporting self-employment and small-scale entrepreneurship: potential programs to improve livelihoods for vulnerable workers. IZA Journal of Labor Policy, 5(1), 1-26. doi:10.1186/s40173-016-0060-2
Chung, J, Gulcehre, C, Cho, K, & Bengio, Y. (2014). Empirical evaluation of gated recurrent neural networks on sequence modeling. arXiv preprint arXiv:1412.3555. https://doi.org/10.48550/arXiv.1412.3555
Coelli, T. J, Rao, D. S. P, O'Donnell, C. J, & Battese, G. E. (2005). An introduction to efficiency and productivity analysis. Springer Science & Business Media. https://link.springer.com/book/10.1007/b136381
Dabbous, A, Barakat , K, & Kraus, S. (2023). The impact of digitalization on entrepreneurial activity and sustainable competitiveness: A panel data analysis. Technology in Society, 73 (02224), 1-13. doi:10.1016/j.techsoc.2023.102224
Dabić, M, Maley, J, Švarc, J, & Poček, J. (2023). Future of digital work: Challenges for sustainable human resources management. Journal of Innovation & Knowledge, 8(2), 100352-100362. doi:10.1016/j.techsoc.2023.102224
dashtban farooji, S. (2015). Survey Relation between Economic Growth, Development of Banking Sector and Macroeconomic Variables with Panel-Var Method, Case Study D8 Countries. Quarterly Journal of Quantitative Economics, 12(4), 39-65. (in persian). doi:10.22055/jqe.2015.12103
Devlin, J, Chang, M. W, Lee, K, & Toutanova, K. (2018). Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805. https://doi.org/10.48550/arXiv.1810.04805
Drucker, H, Burges, C. J, Kaufman, L, Smola, A. J, & Vapnik, V. (1997). Support vector regression machines. Advances in Neural Information Processing Systems,9,155-161.

https://www.researchgate.net/publication/309185766_Support_vector_regression_machines
Du, J, & Nguyen, B. (2019). Cognitive financial constraints and firm growth. Small Business Economics, 58, 2019-2137. doi:10.1007/s11187-021-00503-7.
Effiong, U. E, Ekpe, J. P, & Udofia, M. A. (2022). An Empirical Examination of the Influence of Private Sector Credit on Unemployment in Nigeria. International Journal of Academic Multidisciplinary Research, 6(9), 187-199. https://www.researchgate.net/publication/364011792_An_Empirical_Examination_of_the_Influence_of_Private_Sector_Credit_on_Unemployment_in_Nigeria.
Eide, E, & Showalter, M. (2021). Human Capital. International Encyclopedia of Education (Third Edition), 282-287. doi:10.1016/B978-0-08-044894-7.01213-6
Elhorst, J. P. (2010). Applied spatial econometrics: Raising the bar. Spatial Economic Analysis, 5(1), 9-28. https://doi.org/10.1080/17421770903541772
Elhorst, J. P. (2014). Spatial econometrics: From cross-sectional data to spatial panels. Springer. https://link.springer.com/book/10.1007/978-3-642-40340-8
Elman, J. L. (1990). Finding structure in time. Cognitive science, 14(2), 179-211. https://doi.org/10.1207/s15516709cog1402_1
Evans, D. S, & Jovanovic, B. (1989). An estimated model of entrepreneurial choice under liquidity constraints. Journal of political economy, 97(4), 808-827. doi:10.1086/261629
Fassmann, H. (2001). Spatial Labor Markets. International Encyclopedia of the Social & Behavioral Sciences, 14800-14804. doi:10.1016/B0-08-043076-7/02559-6
Fingleton, B., & Le Gallo, J. (2008). Estimating spatial models with endogenous variables, a spatial lag and spatially dependent disturbances: Finite sample properties. Journal of Geographical Systems, 10(3), 319-354. DOI:10.1111/j.1435-5957.2008. 00187.x
Frankel, J. A, & Romer, D. H. (1999). Does trade cause growth?. American Economic Review, 89(3), 379-399. DOI: 10.4324/9781315254166-11
Freund, Y, & Schapire, R. E. (1997). A decision-theoretic generalization of on-line learning and an application to boosting. Journal of Computer and System Sciences, 55(1), 119-139. https://doi.org/10.1006/jcss.1997.1504
Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. Annals of Statistics, 29(5), 1189-1232. https://doi.org/10.1214/aos/1013203451
Gal, Y, & Ghahramani, Z. (2016). A theoretically grounded application of dropout in recurrent neural networks. In Advances in neural information processing systems.1019-1027. https://doi.org/10.48550/arXiv.1512.05287

Gancia, G, & Zilibotti, F. (2005). Chapter 3 Horizontal Innovation in the Theory of Growth and Development. Handbook of Economic Growth, 1(A), 111-170. doi:10.1016/S1574-0684(05)01003-8

Ghavidel, S; (2008). Factors of Self-Employment in Iran Labour Market. Economic research (sustainable growth and development); 8 (1), 21-41 (in persian). http://ecor.modares.ac.ir/article-18-10566-en.html

hallaji, A, Ghavidel, S, Soufi Majidpour, M, & Heydari, A. A. (2024). Estimating the supply of and demand for labor force until 2050 in Iran. Economic Research (Sustainable Growth and Development), QJER, 24(1), 253-282. (in persian). doi:10.22034/24.1.255

Hariram, N. P, Mekha, K. B, Suganthan, V, & Sudhakar, K. (2023). Sustainalism: An Integrated Socio-Economic-Environmental Model to Address Sustainable Development and Sustainability. Sustainability, 5(13), 10682. doi:org/10.3390/su151310682

Hartigan, J. A, & Wong, M. A. (1979). Algorithm AS 136: A k-means clustering algorithm. Journal of the Royal Statistical Society. Series C (Applied Statistics), 28(1), 100-108. http://www.jstor.org/page/info/about/policies/terms.jsp

Hassanali, & Nasir, R. N. (2024). Efficiency of Microfinance Banks and Microfinance Institutions: In Creating Self-Employment in Pakistan. International Journal of Management and Emerging Sciences Research, 13(4), 24-51. https://doi.org/10.56536/m22jnf66

Haykin, S. (2009). Neural networks and learning machines (3rd ed.). Pearson. https://dai.fmph.uniba.sk/courses/NN/haykin.neural-networks.3ed.2009.pdf

Herkenhoff, K, Phillips, G. M, & Cohen-Cole, E. (2021). The impact of consumer credit access on self-employment and entrepreneurship. Journal of Financial Economics, 141(1), 345-371. https://doi.org/10.1016/j.jfineco.2021.03.004

Hinton, G. E, & Salakhutdinov, R. R. (2006). Reducing the dimensionality of data with neural networks. science, 313(5786), 504-507. https://www.science.org/doi/10.1126/science.1127647

Hinton, G. E, Osindero, S, & Teh, Y. W. (2006). A fast-learning algorithm for deep belief nets. Neural Computation, 18(7), 1527-1554. DOI: 10.1162/neco.2006.18.7.1527

Hochreiter, S, & Schmidhuber, J. (1997). Long short-term memory. Neural computation, 9(8), 1735-1780. DOI: 10.1162/neco.1997.9.8.1735

Hoseinpour Naderi, M, & Alijani, F. (2024). The Impact of Bank Credits on Employment in Iran's Agricultural Sector With an Emphasis on the Role of Bank Ownership. Economic Growth and Development Research, 14(56), 25-42. (in persian). doi: 10.30473/egdr.2024.69131.6773

Imai, K. S, Gaiha, R, Thapa, G, and Annim, S. K. (2012). Microfinance and Poverty- A Macro Perspective. World Development Elsevier, 40(8), 1675-1689.DOI: 10.1016/j.worlddev.2012.04.013

Ioffe, S, & Szegedy, C. (2015). Batch normalization: Accelerating deep network training by reducing internal covariate shift. In International conference on machine learning. 448-456.https://doi.org/10.48550/arXiv.1502.03167

Jain, A., Nandakumar, K., & Ross, A. (2005). Score normalization in multimodal biometric systems. Pattern Recognition, 38(12), 2270-2285. https://doi.org/10.1016/j.patcog.2005.01.012

Kananurak, P, & Sirisankanan, A. (2020). Financial development and self-employment. International Journal of Development Issues, 19(3), 339-357. https://doi.org/10.1108/IJDI-11-2019-0190

Kannapalan, Kumudhini, (2024). Contribution of Self Employment Loans in Livelihood Improvement Entrepreneurship & Economics eJournal Available at SSRN. 18(49), 1-17. https://ssrn.com/abstract=4905036 or http://dx.doi.org/10.2139/ssrn.4905036

Kim, G. (2007). The analysis of self-employment levels over the life-cycle. The Quarterly Review of Economics and Finance, 47(3), 397-410. doi: 10.1016/j.qref.2006.06.004

Kingma, D. P, & Ba, J. (2014). Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.

Kingma, D. P, & Welling, M. (2013). Auto-encoding variational bayes. arXiv preprint arXiv:1312.6114.

Kipf, T. N, & Welling, M. (2017). Semi-supervised classification with graph convolutional networks. arXiv preprint arXiv:1609.02907.

Klapper, L, Laeven, L, & Rajan, R. (2006). Entry regulation as a barrier to entrepreneurship. Journal of financial economics, 82(3), 591-629. doi: 10.1016/j.jfineco.2005.09.006

Kunawotor, M, & Ahiabor, G. (2024). Self-employment, financial access and economic well-being: Empirical evidence from Africa. Journal of Financial Economic Policy. 16(20), 56-79. https://doi.org/10.1108/JFEP-03-2024-0087.

Le, A. (2002). Empirical Studies of Self-Employment. Journal of Economic Surveys, 13(4), 381-416. doi:10.1111/1467-6419.00088.

LeCun, Y, Bottou, L, Bengio, Y, & Haffner, P. (1998). Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11), 2278-2324. DOI: 10.1109/5.726791

LeSage, J, & Pace, R. K. (2009). Introduction to spatial econometrics. CRC press. https://www.researchgate.net/publication/339938974_LeSage_Pace_2009_Introduction_to_Spatial_Econometrics_Statistics_A_Series_of_Textbooks_and_Monographs

Liaw, A, & Wiener, M. (2002). Classification and regression by randomForest. R News, 2(3), 18-22. https://www.researchgate.net/publication/228451484_Classification_and_Regression_by_RandomForest

Looi Kee, H, & Chen, D. (2005). A Model on Knowledge and Endogenous Growth. SSRN Electronic Journal, 1(28), 1-24. doi:10.2139/ssrn.678901

MacQueen, J. (1967). Some methods for classification and analysis of multivariate observations. Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability, 1(14), 281-297. https://www.scirp.org/reference/referencespapers?referenceid=2232949

McCulloch, W. S, & Pitts, W. (1943). A logical calculus of the ideas immanent in nervous activity. The bulletin of mathematical biophysics, 5(4), 115-133. https://doi.org/10.1007/BF02478259

McDaniel, B. (2005). A Contemporary View of Joseph A. Schumpeter's Theory of the Entrepreneur. Journal of Economic Issues, 39(2), 485-490. doi:10.1080/00213624.2005.11506826

McKernan, S.-M. (2002). The Impact Of Microcredit Programs On Self-Employment Profits: Do Noncredit Program Aspects Matter? Review of Economics and Statistics, 84(1), 93-115. doi:10.1162/003465302317331946

Menon, N, & Rodgers, Y. (2013). Credit and self-employment. Handbook of Research on Gender and Economic Life, 22, 359-377. doi:10.4337/9780857930958.00035

Mohamed, H, Mirakhor, A, & Erbaş, S. (2019). Chapter 2 - Theoretical Frameworks. Belief and Rule Compliance, An Experimental Comparison of Muslim and Non-Muslim Economic Behavior(Perspectivs in Behavioral Economics and the Economics of Beh), 7-41. doi:org/10.1016/B978-0-12-813809-0.00002-3

Mohammadi, H, Karim, M. H, Samare Hashemi Shabjare, K, & Sargazi, A. (2019). The Effects of Economic Shocks on Labor Market in Iran. Quarterly Journal of The Macro and Strategic Policies, 7(26), 268-285. (in persian). doi:10.32598/JMSP.7.2.268

Muñoz-Céspedes, E, Ibar-Alonso, R, & Cuerdo-Mir, M. (2024). Individual entrepreneurial behavior and financial literacy. Int Entrep Manag J, 20, 2263-2285. doi:10.1007/s11365-023-00936-4

Nair, V, & Hinton, G. E. (2010). Rectified linear units improve restricted boltzmann machines. In Proceedings of the 27th international conference on machine learning. 10(1), 807-814. https://dl.acm.org/doi/10.5555/3104322.3104425.

Narita, R. (2020). Self-employment in developing countries: A search-equilibrium approach. Review of Economic Dynamics, 36, 1-34. doi:org/10.1016/j.red.2019.04.001

Nielsen, D. (2016). Tree boosting with XGBoost-why does XGBoost win "every" machine learning competition? (Master's thesis, NTNU). http://hdl.handle.net/11250/2433761

Nikpey, V., & Mohammadzadeh, Y; Rezazadeh, A; Ansari Samani, H. (2024). Spatial analysis of dependency culture resulting from exchange rate fluctuations on herding behavior in Iran's housing market. International

Journal of Housing Markets and Analysis. https://doi.org/10.1108/IJHMA-09-2024-0137
Olowofeso, E. O, Adeleke, A. O, & Udoji, A. O. (2015). Impact of private sector credit on economic growth in Nigeria. CBN Journal of Applied Statistics, 6(2), 81-101. Retrieved from hdl.handle.net/10419/142107
Pascanu, R, Mikolov, T, & Bengio, Y. (2013). On the difficulty of training recurrent neural networks. In International conference on machine learning. 1310-1318.https://doi.org/10.48550/arXiv.1211.5063
Pham, T, Talavera, O, & Zhang, M. (2018). Self-employment, financial development, and well-being: Evidence from China, Russia, and Ukraine. Journal of Comparative Economics, 46(3), 754-769. https://doi.org/10.1016/j.jce.2018.07.006
Prechelt, L. (1998). Early stopping-but when? In Neural Networks: Tricks of the trade (pp. 55-69). Springer. https://link.springer.com/chapter/10.1007/3-540-49430-8_3
Quayes, S. (2012). Depth of Expansion and Financial Sustainability of Microfinance Institutions. Applied Economics, 44(26), 3421-3433. DOI: 10.1080/00036846.2011.577016
Quinlan, J. R. (1986). Induction of decision trees. Machine Learning, 1(1), 81-106. http://dx.doi.org/10.1007/BF00116251
Rashidardeh, H, Khazaei, S, Zanjani, M, & Vali, M. (2017). The Future of Iran's Banking Industry with a Scenario Approach. Straitegic Management Studies, 8(30), 65-89. (in persian). Retrieved from civilica.com/doc/916494
Rumelhart, D. E, Hinton, G. E, & Williams, R. J. (1986). Learning representations by back-propagating errors. Nature, 323(6088), 533-536.
Saeedi, Parviz (2012). Investigating the impact of bank credit on employment. Journal of Macroeconomics. 14(2), 85-102 (in Persian). https://jes.journals.umz.ac.ir/article_65_33a9e17a9c4d103227ca739257b7a8c3.pdf
Salas, V, Sanchez-Asin, J, & Storey, D. (2014). Occupational choice, number of entrepreneurs and output: Theory and empirical evidence with Spanish data. Journal of the Spanish Economic Association, 5(1), 1-24. doi:10.1007/s13209-013-0103-5
Sarani, N, Sharifzadeh, M. S, Abdollahzadeh G. 2024. Impact Assessment of Micro- cre dit on Livelihood of Rural Households: Implications for Self-employment and Micro- entrepreneurship in the Light of Islamic-Iranian Model of Progress. Journal of Studies in Entrepreneurship and Sustainable Agricultural Development, 11 (2), 141-160. (in Persian). DOI: 10.22069/jead.2023.21633.1747
Scarselli, F, Gori, M, Tsoi, A. C, Hagenbuchner, M, & Monfardini, G. (2009). The graph neural network model. IEEE Transactions on Neural Networks, 20(1), 61-80. https://ieeexplore.ieee.org/document/4700287
Scherer, D, Müller, A, & Behnke, S. (2010). Evaluation of pooling operations in convolutional architectures for object recognition. In International

conference on artificial neural networks. 92-101. DOI: 10.1007/978-3-642-15825-4_10

Shahabadi, Abolfazl, and Khatami, Tayyebeh. (2013). Determinants of Self-Employment in the Iranian Economy. Journal of Sustainable Growth and Development (Economic Research), 13(1), 91-109. (in Persian). https://sid.ir/paper/86622/fa

Smola, A. J, & Schölkopf, B. (2004). A tutorial on support vector regression. Statistics and Computing, 14(3), 199-222. https://alex.smola.org/papers/2004/SmoSch04.pdf

Sohaili, K, Fatahi, S, & mohammadi, S. (2018). Investigating the role and effects of private and public investment on employment in provinces of Iran: GMM approach. Macroeconomics Research Letter, 12(24), 121-148. doi: 10.22080/iejm.2018.1940

Srivastava, N, Hinton, G, Krizhevsky, A, Sutskever, I, & Salakhutdinov, R. (2014). Dropout: a simple way to prevent neural networks from overfitting. The journal of machine learning research, 15(1), 1929-1958. https://jmlr.csail.mit.edu/beta/papers/v15/srivastava14a.html

Sundbo, J. (2015). Innovation, Theory of. International Encyclopedia of the Social & Behavioral Sciences (Second Edition), 169-174. doi:10.1016/B978-0-08-097086-8.32075-X

Taheri Haftasiabi, R, mohammadzade, y; Naderi, a; (2024). Prediction of the impact of bank failure risk on micro-credit in Iran: an artificial intelligence approach. International Journal of Management, Accounting and Economics (IJMAE). 11(12), 1-19. https://www.ijmae.com/article_210440.html

Tayyibi, Seyed Kamil, and Abbaslou, Yaser. (2009). Bank Credit and Other Economic Determinants of the Business Environment in Iran. Money and Economy, -(1), 57-78. (in Persian). https://sid.ir/paper/168092/fa

Thurik, R, Carree, M, van Stel, A, & Audretsch, D. (2008). Does Self-Employment Reduce Unemployment? SSRN Electronic Journal, 23(6), 673-686. doi:10.1016/j.jbusvent.2008.01.007

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. Journal of the Royal Statistical Society: Series B (Methodological), 58(1), 267-288.

Uiku, H. (2004). R&D, Innovation, and Economic Growth: An Empirical Analysis. International Monetary Fund, 04(185), 1-37. Retrieved from https://www.imf.org/external/pubs/ft/wp/2004/wp04185.pdf

Vaswani, A, Shazeer, N, Parmar, N, Uszkoreit, J, Jones, L, Gomez, A. N, ... & Polosukhin, I. (2017). Attention is all you need. In Advances in neural information processing systems. 5998-6008. https://doi.org/10.48550/arXiv.1706.03762

Vincent, P, Larochelle, H, Bengio, Y, & Manzagol, P. A. (2008). Extracting and composing robust features with denoising autoencoders. In Proceedings of the 25th international conference on Machine learning.1096-1103. DOI: 10.1145/1390156.1390294

Virk, A, Nelson, E.-U, & Dele-Adedeji, I. (2023). The challenge of youth unemployment in Nigeria. Journal of International and Comparative Social Policy, 39(3), 319–329. doi:10.1017/ics.2024.4

Willis, D, Hughes, D, Boys, K, & Swindall , D. (2020). Economic growth through entrepreneurship: Determinants of self-employed income across regional economies. Papers in Regional Science, 99(1), 73-96. doi:10.1111/pirs.12482

World Bank. (2021). World Development Indicators. https://data.worldbank.org/

Zou, H, & Hastie, T. (2005). Regularization and variable selection via the elastic net. Journal of the Royal Statistical Society: Series B (Statistical Methodology), 67(2), 301-320. https://doi.org/10.1111/j.1467-9868.2005.00503.x