Timely repayment of agricultural loans: Evidence from Serbian farmers

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Abstract

Our study aimed to determine factors influencing the timely loan repayment of smallholder farmers. We used data from 1735 liquidated loans, collecting a set of 36 feasible determinant variables. The study was two-folded. In the first step, with a 64% accuracy, a Logit model revealed 18 significant predictors of timely repayment. Previously credited clients, special agricultural accounts, average monthly inflow, loan amount, age when applying for a loan, clean credit history, and no credit in the past have a positive influence. In contrast, the number of transactions, profiling, owned farm area, past due records over five days, tax debt status, and livestock negatively influenced timely repayment. In the second step, we used machine learning algorithms to enhance model prediction performance. XGBoost model has envisioned timely repayment with 92% accuracy. As significant predictors, Shapley's additive explanations identified clean credit history, average monthly inflow, time of owning the account, age when applying for a loan, and horticulture. The study's findings provide insight into the critical factors in substantially achieving a high repayment rate on borrowed funds.

Keywords: Agricultural loans, Timely repayment, Smallholder farmers, Banks, Machine learning algorithms

1. Introduction

Agriculture is among the world's largest industries and is paramount for economic prosperity and development. It is described as a backbone and the primary sector of the industry for many countries in the world (Murungi *et al.*, 2023; Pejak *et al.*, 2022), as well as a critical link in the food supply chain (Đokić *et al.*, 2022). Growth in this sector is two to four times more efficient in raising incomes among the poorest than other sectors (World Bank, 2023). In terms of economic growth, according to the World Bank report, agriculture accounts for 4% of global GDP; in some developing countries, it can even account for more than 25% of GDP (World Bank, 2023). Since the world population is projected to increase to nine billion people by the year 2050, specific estimates indicate that agricultural production will have to increase by at least 70% (Ljubičić *et al.*, 2023; Maricic *et al.*, 2016; McKenzie and Williams, 2015).

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Despite its importance, sustaining a business in this sector is difficult, especially for small local farmers. One of the main reasons is insufficient assets for funding a business, and among the various factors contributing to low profitability of agriculture, the foremost is lack of access to credit (Bharti, 2018). Farmers often require considerable loans to transform their agricultural business into a profit-oriented farm business (Rathore *et al*., 2017). Thus, there is undoubtedly a need for improving access to agricultural financing for producers (Kusek *et al*., 2017). Unfortunately, despite the high demand for agricultural loans, financial institutions tend to avoid them, particularly for small local farmers (Kong and Loubere, 2021).

Different authors have even determined that state support is needed to provide the agricultural industry with affordable long-term lending resources and introduce referential credit mechanisms for agricultural commodity producers (Poliatykina *et al*., 2022, p. 126). In Serbia, for example, there has been a considerable improvement in the quality and volume of institutional support for developing the small and medium enterprises (SME) sector in all activities. Thus, with appropriate agrarian policy instruments, the business performance of SMEs in agribusiness is being improved year by year (Jovanović and Zubović, 2019).

The other side represents banks' risk when approving agricultural loans. Banks often encounter the problem of loans that are not repaid on time or fully repaid at all. For financial institutions, the recovery of agricultural loans is often crucial because timely repayment ensures the recycling of funds and strong confidence among the parties (Rathore *et al*., 2017). Also, it helps farmers trust in their ability to develop their business. Various factors, including government policies, demographics, institutional, cultural, and environmental elements, directly and indirectly impact loan repayment (Sileshi *et al*., 2012). Swift repayment of credit is crucial for maintaining good creditworthiness. Consequently, the inability of borrowers to repay their loans is a critical concern for the long-term viability of credit institutions (Kassegn and Endris, 2022). Our research particularly strives to determine the factors influencing the timely repayment of agricultural loans.

Most banks have a problem calculating creditworthiness for clients who do not have financial reports, i.e. audit reports. For clients with balance sheets, it is relatively easy. Banks apply standardized procedures in line with Basel II adopted principle of risk management. Still, the main challenge comes when the customer does not have an official financial report – which is often the case with small farmers in many countries. In that case, some banks on the market usually do not provide loans for this client segment, or if they do, they develop some internal methodology and logic which must be in line with Basel II and approved by the national bank of the local county. This is precisely the situation we investigate in our paper: a large group of small producers, approximately 449,000 of them, without financial reports but with a real need for investments in their agricultural production. Government subsidies and guaranty schemes can cover one part of their needs, but producers must also use commercial bank loans.

In the Serbian market, it is not possible to insure the debt of small agricultural producers to the bank. Still, despite that fact, commercial banks have provided working capital and investment loans to producers very actively for the last 20 years. In general, the National Bank of Serbia supports the development of new credit products for agricultural producers because it is apparent that they are in continuous need of them.

Credit in Serbia policy reveals that the budget for subsidies in agriculture is growing every year. The government is providing cheap or free loans for investments and working capital (WC) and 30% to 50% cash back (grants) for defined types of investments in agriculture. The most subsidy types of investments are new tractors, machinery, irrigation systems, and hail nets. In 2024, the Ministry of Agriculture's most significant budget for cattle and milk production (around 70%) is proposed. In general, Agricultural unions - cooperatives also provide, in some cases, benefits for farmers by postponing payments up to 12 months for WC or smaller machinery. The Ministry of Agriculture and the European Union (EU) are the main supporters of direct finance to small farmers.

We performed a study in the Serbian region, in one of the central banks that provides agricultural loans to small farmers. Although agriculture plays a crucial role in Serbia, the sector faces challenges such as outdated equipment, fragmentation of holdings, lack of modern technologies, and problems in the distribution and marketing of products. Serbia is located on a total area of 8,840 thousand hectares. The area of agricultural land includes 5,734 thousand hectares, and around 4,867 thousand hectares of that area is arable land. There are over 450 thousand smallholder farmers in Serbia. When it comes to context analysis of agricultural needs in Serbia, according to data from the Credit Bureau (CB), only 10% of smallholder farmers use loans, and around 30% of legal entities in agro-businesses use loans. Generally, 80% of approved loans are used for WC, such as seeds, fertilizers, chemistry, etc., and just 20% for investment purposes. Around 30% of small farmers postpone paying (up to 6 months) provided by the distributor of WC. In the coming years, the use of loans will increase because distributors will slowly postpone paying services. Serbia's challenge is finding a balance that increases loan accessibility without compromising responsible lending practices or violating regulatory requirements. Striking this balance can help foster financial inclusion while mitigating the associated risks. One of the pre-requirements of increasing access to loans is the profound insight into their timely repayment.

This study aims to determine the significant drivers of timely repayment of agricultural bank loans. The results could help distinguish between lenders who would be acceptable and those who would possibly have problems with the repayment of loans (Hardy and Weed, 1980). To create the appropriate model, we derived an extensive series of latent input variables, which are specific and unique to the agricultural sector. We imported the latent inputs into the logit model to extract the most crucial input variables, predict timely repayment, and interpret the results justly. We later developed machine learning algorithms to enhance the performance of the model prediction.

The next chapter offers a literature review on agricultural loans and timely repayment. The following chapters briefly describe the methodology, the study results, and the discussion. Finally, the conclusions of the study are given.

2. Literature Review

Advancements in agriculture significantly contribute to the availability, accessibility, and stability of food resources. The Economist Intelligence Unit has developed The Global Food Security Index (GFSI), measuring the level to which countries provide safe food to their citizens (Izraelov and Silber, 2019; Maricic *et al*., 2016). Chavas *et al*. (2022) have analyzed the yield risk and its implications for the economics of food security. They have investigated agricultural diversification throughout different regions in Italy and found a close relationship between agricultural development and reductions in food insecurity (Chavas *et al*., 2022). According to the authors, agricultural technology has been a key driver in reducing food insecurity through increasing food production and reducing risk exposure in agriculture.

One of the most significant problems of agricultural development is the lack of access to finance (Endris and Kassegn, 2023; Mirč *et al*., 2023; Ozalp, 2019), which is majorly contributing to low profitability in agriculture (Bharti, 2018). Many of the bank's rules and regulations disadvantage farmers' ability to access finance because of a lack of collateral, regulatory matters, lending criteria, and the short timeframe for land leases, thus predominantly affecting production (Amadhila and Ikhide, 2016). As Huang and Wang (2014) show, agriculture is much underinvested. In developing countries, domestic and foreign aid has not increased appropriately to maintain sustainable agriculture (Huang and Wang, 2014). Moreover, transitioning to sustainable agricultural systems is imperative to meet the global Sustainable Development Goals (SDGs). However, achieving more sustainable agricultural production systems will require significant additional capital (Havemann *et al*., 2020; Xia *et al*., 2022).

Agricultural loans affect the value of agricultural production (Chandio *et al*., 2018; Kadanali and Kaya, 2020). Besides savings and insurance prod-

ucts, credits largely influence the capacity of small local farmers and are crucial for inclusive finance and sustainable agricultural production (Peprah *et al*., 2021). In developing countries, smallholder farmers face two significant barriers to agricultural investment: weather-related risk and credit. In that sense, rural areas suffer from several financial market imperfections that hinder credit market access and agricultural investment, particularly among smallholders (Mishra *et al*., 2021).

Agricultural loans have been studied worldwide. Kaya and Kadanalı (2022) found indications that the effect of agricultural loans in Turkey has increased over the past time, and the deposit banks have a high impact on agricultural production. Moreover, the ratio of agricultural credits to total loans in Turkey has increased from 3% to 6% between 1999 and 2014, and during this process, new actors, such as private banks, agricultural lenders, agricultural product marketing firms, etc., have entered the agricultural credit market (Kusek *et al*., 2017). In China, the government has taken measures to increase access to agricultural loans to improve farmers' social welfare (Feder *et al*., 1989; Gong and Elahi, 2022). For example, rural land management mortgage loans can enable farmers to gain more credit funds, which is conducive to agricultural development and revitalization (Zheng and Zhang, 2021). China has successfully achieved its intended policy goal of boosting the agriculture sector (Lin and He, 2020). Also, through fiscal incentives, financial institutions are encouraged to increase agricultural loan offers, leading to a significant decline in urban-rural income inequality, particularly in underdeveloped areas of China (Tang and Sun, 2022).

On the other hand, credit availability is much lower in less developed countries. Agricultural credit is a significant factor in the Indian agricultural sector (Behera and Behera, 2022). Still, credit utilization for productive purposes is limited due to the frequent abuse for nonagricultural purposes (Rathore *et al*., 2017). In Nigeria, the agricultural sector is characterized by low productivity due to the lack of modern technologies, and poor access to credit is seen as a critical barrier to their adoption (Balana and Oyeyemi, 2022). One of the main challenges the agricultural banks

in Iran encounter is the high probability of repayment failure (Pishbahar *et al*., 2015). In Ghana, the mistrust of financial institutions in small local farmers is seen through activities such as requesting enormous collateral, guarantors, high savings, high interest rates for agriculture loans, delinquency, and bureaucratic processes in accessing loans (Teye and Quarshie, 2022).

Some authors propose introducing insured loan products to increase credit market access through an increase in the supply of credit (Mishra *et al*., 2021). Teye and Quarshie (2022) suggested that enabling policy environment and frameworks with supportive rural infrastructure, such as warehouse receipt systems, can make major increases in farmers' access to loans for investment in modern technologies, which can further increase agricultural productivity, essential to address issues of food uncertainty and rural poverty in Ghana. Some authors propose blended finance as a novel alternative to financing the agricultural sector (Dey and Mishra, 2022).

In the past, for example, private banks typically had little interest in agricultural finance. Thus, states became lenders of last resort for local farmers, setting up agricultural finance institutions (Martin and Clapp, 2015). The state hence played a crucial role in providing agricultural credit and capital to farmers, and, importantly, the state protected banks and finance by preventing foreclosures and other losses on loans (Martin and Clapp, 2015; Onyiriuba *et al*., 2020). In Azerbaijan, for example, agriculture financing has positive potential since the government provides financial support through investments and loans that may positively affect farmers' financial sustainability and competitiveness (Humbatova and Hajiyev, 2021). However, given that government subsidies and banking loans do not always provide sufficient funds, according to some authors, new sources of financing are in need, and Mirovic and Bolesnikov are pointing out the possibilities of applying asset securitization in financing agriculture (Mirović and Bolesnikov, 2013).

Agricultural credit is characterized not only by the approval of the loan but also by its timely repayment. The effective performance of financial institutions can only be judged when the farm-

er-borrowers repay their loans and when they fall due to the farm credit agency (Rathore *et al*., 2017).

Timely loan repayment is an essential issue in all sectors. Increasing the number of payment loan models is vital for financial institutions to attract more clients (Eroglu and Ozturk, 2016). To ensure approved loan repayment, they adapt innovations and new technologies to payment intermediation (Miglionico, 2023). It was common for bank clients to desire not to make payments in some periods because of income uncertainty over time. Formato (1992) and Moon (1994) used this to study the models of arbitrary skips.

Jet, when it comes to agricultural loans, the determinants of timely repayment are pretty specific. Olagunju has, for example, found that a ration rate, among others, was an important factor in ascertaining the rate of repayment at different significant levels for crop farmers, leading to a conclusion that credit rationing did have a positive influence on agricultural credit repayment (Olagunju *et al*., 2023). When observing the size of local farmers, findings show that, compared to medium farmers, marginal and small farmers diverted a portion of the loans. The extent of loan repayment by medium farmers was higher than that of small and marginal farmers (Ray and Das, 2023). A study by Amedi, Dumayiri, and Mohammed (2019) showed that the factors that significantly influence loan repayment are sex, household size, group size output value, and loan disbursement timeliness. Moreover, over-indebtedness was found to be higher among the more experienced farmers and the farmers having more percentage of cash crop and with the increase of overdue amount and credit demand per acre, but lower with the rise of per acre cost for production (Das and Sharma, 2023).

Pishbahar and his coworkers found that extra activities besides farming, the extension of the loan repayment period, and a large volume of received loans were the causes that had significant negative impacts on loan repayment. On the other hand, causes like high interest rates of loans, existing collaterals or different types of guarantors, services received from the banks, and long-term maturity periods significantly boost the probability of timely loan repayment (Pishbahar *et al*., 2015). Other methods, such as

crop insurance, protect lenders by increasing the likelihood of loan repayment when revenue declines (Ifft *et al*., 2023). Agricultural insurance can positively affect agricultural loans by reducing the risk for lenders, thereby encouraging more favourable loan terms and increasing credit availability to farmers. However, some authors have found that crop subsidies negatively impact farmers' insurance policies and premiums, with public aid disincentivizing agricultural insurance, leading to their low penetration, which is the case in Italy (Miglietta *et al*., 2020).

According to the Common Agricultural Policy (CAP), the EU promotes food security and sustainable farming by providing income support to farmers. CAP Strategic Plans support the resilience of the agricultural sector by supporting viable farm income through direct payments to active farmers (European Commission, 2024). CAP financial instruments have significant potential to contribute to the "Farm to Fork" and "Biodiversity strategies", but the financial needs of agriculture and the agri-food sector remain high. In Poland, for example, the permanent domination of the subsidies under CAP and its first pillar (market management and income support) radically narrows the space for using financial instruments (Kulawik *et al*., 2018). To receive total payments under the first pillar, farmers must comply with cross-compliance, which covers statutory management requirements and standards for good agricultural and environmental conditions and the requirements of 'greening' (Heyl *et al*., 2021). Kulawik *et al*. (2018) consider that financial instruments under the CAP are adjusted mainly to achieve allocation and stabilisation objectives and that only larger farms may be interested in them. Staniszewski and Borychowski (2020) have also found that the impact of subsidies on efficiency depends on the size of farms and that the significant, stimulating effect of subsidies was identified only in the group of the largest farms. Thus, even in the EU, it is more difficult for smallholder farmers to manage. Serbia has over 85% of small-sized agricultural companies, while only 1.5% are large farmers.

As Western Balkan (WB) countries are in the process of integration into the EU, agricultural

efficiency and the actuality of the problems of the agricultural sector are paramount (Đokić *et al*., 2022). Still, as the same authors show, there is a significant difference in technical efficiency between WB and the EU, which is significantly lower in WB. This might be an alarm for policymakers in the WB, in the sense that agricultural policy measures should encourage more intensive agricultural production, which could create a better foundation for agricultural growth (Matkovski *et al*., 2022).

Agriculture is essential in Serbia's economy, with a high share of the Gross Domestic Product (GDP), which, according to the World Bank, was 6.29% in 2021 (Radulović *et al*., 2023). In a study on micro-sized, small-sized, and medium-sized agricultural companies in Serbia, results indicate that the micro-sized agricultural companies were at greater risk of bankruptcy. In contrast, small- and medium-sized companies were more stable (Milić *et al*., 2022). Regarding the reliability of reported earnings of agricultural companies in Serbia, profitability and leverage significantly influence the scope and direction of earnings management. Income-decreasing behaviour is observed in more profitable firms, while income-increasing behaviour is observed in highly leveraged and more profitable firms (Milić *et al*., 2018). Further, Tekic *et al*. (2021) studied the model of agricultural loan approval in Serbia. They have found, from several models, that consistent factors influencing loan approval were profitability and solvency of the smallholders (Tekić *et al*., 2021).

As mentioned before, the agricultural land area in Serbia is more than 5.7 million hectares, and more than 4.8 million hectares of that area is arable land. The most developed branches of agriculture are animal husbandry (43%) and arable farming (42%), followed by fruit growing and viticulture (12%), while other crops are represented by 3%. Family farming and private ownership (smallholders) dominate, while the average size of a commercial farm (enterprise) is 500 to 700 hectares. Family farming is fragmented and has a pronounced natural consumption and a significantly lower degree of commercialization than European farms. Approximately 600 thousand tractors, 38 thousand harvesters, and

Table 1 - Number of loans of smallholder farmers in Serbia.

Date	Number of loans	Number of clients
December 31, 2022	70,545	45,522
November 30, 2023	68,348	43,747

Data source: CB (2023)

more than 3 million attachment machines cultivate agricultural land (SORS, 2023a). Regarding livestock, according to data from 2018, there were a total of 424,155 dairy cows, 3,266,102 pigs, 1,799,814 sheep, and 218,397 goats (SORS, 2023b). In Serbia, the irrigation system is installed on 180 thousand hectares. Still, only 30-40 thousand hectares are irrigated, which, together with gardens and some newer systems, represents less than 1% of the arable land.

From more than 450 thousand registered agricultural holdings in Serbia, out of which 433,217 are active, barely 10% use loans. Table 1 shows the number of loans for smallholder farmers in Serbia.

As a candidate country for membership in the EU, Serbia is working to harmonize its agricultural policy with European standards to improve the competitiveness and sustainability of its agricultural sector. The agricultural market and its upstream food and beverage sector have always been considered the most valuable resource and have tremendous potential that can and should be used. Serbia's most significant traditional comparative advantage lies in favourable climate conditions and rich and fertile land.

3. Methodology

3.1. *Respondents*

Our research observed small local farmers in Serbia. Data were provided by the authors from the OTP bank, one of the largest banks in Serbia, with a highly developed agricultural department. Data contain 1,735 liquidated loans from Serbian smallholders. We observed the *timely repayment* of these loans, representing our primary dependent variable. Of 1,735 loans, 926 were timely repaid, while 809 were defaults. Liquidated loans are dated from 2018 to 2023.

3.2. *Variables and Models*

In this paper, we have modelled the timely repayment of agricultural loans, which represents the binary variable, as noted above. Initially, we extracted a vast set of 36 input variables to evaluate the output. Input variables were chosen for dual reasons. First, it was in accordance with the presented literature review. Second, it was derived from the discussion sessions with leading experts in the bank's agricultural sector.

Input variables include bank data on the client (previously credited client, the average monthly number of salary transactions, profiling, segment, years between the first product approval and a report), data on special account (SA) for agricultural purposes (period of owning SA, SA payment card, period of owning E-bank SA, SA average monthly inflow, SA average monthly number of transactions), client descriptives (age, mail address, employment data availability, occupation, employment status, education), loan data (loan type, loan amount in RSD, related parties), CB data (client's exposure on application date, clean credit history, CB report pulls in 30 days, past due records over five days, no credit in the past, tax debt status, number of credit products), farm data (farm existence in years, farm area, owned farm area, share of owned area, number of crops, number of farm members 18 to 72, farm holder age on application date, farming, horticulture, fruit growing, livestock, other). The input variables encompass a comprehensive range of data, including the clients' banking history, SA details, personal demographics, loan specifics, CB information, and detailed farm data. This diverse set of factors is crucial in assessing the risk and potential for timely loan repayment, as they provide a holistic view of the client's financial stability, creditworthiness, and the operational aspects of their agricultural activities.

We have used a two-fold approach to predict the timely repayment of agricultural loans. Firstly, we used the list of input variables as predictors in the Logistic regression model. The purpose was to obtain an explainable model that would be useful to stakeholders and policymakers. The selected variables that would show the highest importance for predicting timely repayment will be described in detail in the results section.

Secondly, looking up to some authors (Chen *et al.*, 2021; Elnaggar *et al.*, 2020), we have applied machine learning algorithms for prediction. The primary purpose was to downsize the list of our input variables. Based on the evidence on best prediction performance from the literature, the models we have focused on are XGBoost, Random Forests, and Support Vector Machines (Chen *et al.*, 2021; Elnaggar *et al.*, 2020). The results of our analyses are given in the following chapter.

4. Results and Discussion

In the first part of our research, we have created the Logit model for the timely repayment of agricultural loans. As described in the previous section, we have included 36 predictor variables in our model. The following formulas define the model:

$$P_i = \frac{e^{\beta_0 + \sum_{j=1}^{k} \beta_j X_{ji}}}{1 + e^{\beta_0 + \sum_{j=1}^{k} \beta_j X_{ji}}} \quad (1)$$

or

$$L_i = \ln\left(\frac{P_i}{1 - P_i}\right) = \beta_0 + \sum_{j=1}^{k} \beta_j X_{ji} + \varepsilon_i \quad (2)$$

where P_i presents the probability of the i-th client to repay the loan on time, $i=1\ldots n$, L_i presents the Logit model, X_{ji} represents the j-th predictor variable for the i-th client, β_0 represents the constant and β_j represents the coefficient for the j-th predictor variable.

We have performed a backwards Logit modelling to reduce the model to the significant input variables for the prediction. The initial model represents the model with all 36 predictors, while the final model includes 18 predictors. The results of the model are given in Table 2.

The Naglekerke R of the initial model is 0.164, and for the final model is 0.156, which is a bit lower than preferable. However, the omnibus test is statistically significant (p<0.001). At the same time, the Hosmer and Lemeshow Test is not statistically significant (p=0.472 for the initial model and p=0.242 for the final model), which shows that our model is not a bad fit. The overall accuracy of the final model is 64.4%.

The variables shown to be significant for predicting timely repayment in the final Logit model

Table 2 - Results of the Logit model.

Variable	Initial model			Final model		
	B	Wald	Exp(B)	B	Wald	Exp(B)
Constant	1.254	3.820	3.505	1.492	6.812*	4.446
Period of Owning SA (years)	0.003	0.067	1.003			
Previously Credited Client	0.259	2.510	1.296	0.290	4.874*	1.336
Payment Card for SA	0.180	1.787	1.197			
Owning E-Bank SA (years)	0.068	4.075*	1.070	0.073	4.969*	1.075
Average Monthly Inflow to SA (100 EUR)	0.014	5.911*	1.015	0.014	6.297*	1.015
Average Monthly Number of SA Transactions	-0.024	3.967*	0.976	-0.020	3.264	0.981
Profiling in Months	-0.455	5.963*	0.635	-0.470	6.507*	0.625
Age	-0.199	7.256*	0.820	-0.190	7.665**	0.827
Mail Availability	-0.285	4.355*	0.752	-0.265	3.985*	0.767
Employment Data Availability	-0.107	0.425	0.898			
Segment	0.042	0.130	1.043			
Occupation	0.174	2.651	1.190			
Related Parties	-0.163	1.015	0.850			
Loan Type	-0.300	4.042*	0.741	-0.293	4.005*	0.746
Loan Amount (1000 EUR)	0.028	3.725	1.028	0.024	3.126	1.025
Employment Status	-0.179	6.899*	0.836	-0.199	9.841**	0.819
Education	0.021	0.073	1.021			
Farm Existence in Years	-0.001	0.006	0.999			
Farm Area	0.031	0.033	1.032			
Owned Farm Area	-0.008	0.457	0.992	-0.014	2.901	0.986
Share of Owned Area	-0.024	0.015	0.976			
Number of Crops	-0.019	0.774	0.981			
Number of Farm Members 18 to 72	-0.015	0.075	0.985			
Farm Holder's Age When Applying	0.208	7.886**	1.232	0.199	8.377**	1.220
Clean Credit History	0.635	12.878***	1.887	0.622	12.583***	1.862
CB Report Pulls in the Last 30 Days	-0.132	0.155	0.877			
Past Due Records over 5 Days	-0.735	7.532**	0.479	-0.779	8.763**	0.459
No Credit in Past	0.277	4.185*	1.319	0.267	4.349*	1.306
Years Between First Product Approval and Report	5.455	5.960*	234.011	5.642	6.510*	282.145
Tax Debt Status (1000 EUR)	-0.045	4.541*	0.956	-0.047	5.454*	0.954
Number of Credit Products	-0.020	0.869	0.980			
Farming	-0.035	0.040	0.966			
Horticulture	-0.083	0.260	0.921			
Fruit Growing	-0.010	0.003	0.990			
Other	-0.078	0.220	0.925			
Livestock	-0.001	5.151	0.999	-0.002	6.443*	0.998
Goodness of fit measures						
Naglerke R	0.164			0.156		
Omnibus test	227.43***			215.55***		
Hosmer and Lemeshow Test	7.617			10.340		
		Predicted			Predicted	
Confusion matrix		Yes	No		Yes	No
	Yes	68.25%	31.75%	Yes	66.63%	33.37%
	No	39.06%	60.94%	No	38.07%	61.93%

*p<0.05; **p<0.01; ***p<0.001.

include the set of 18 input variables, which will be further discussed. *Previously Credited Client* is a client who has already used the bank's services in terms of credit, and the bank has a lot of data about this client and his repayment history. When the client applies for a loan again, the bank can generate additional interest income and increase client-level profitability. If the previous loan was repaid per the agreed terms, it could increase the bank's faith in the client's ability to meet obligations, reducing the risk of defaulting in the repayment period. This information provides benefits for the bank in terms of reduction of marketing costs – it is more likely that a previously credited client will use the services of the same bank again, which can reduce the need for intensive marketing campaigns to attract new clients; better understanding of credit risk – the bank already has historical data on the client's behavior regarding loan repayment, which enables a better assessment of credit risk and making informed decisions regarding the approval of new loans; personalized offers – bank may use historical data on previous loans to provide customized offers to the client, including better interest rates or other benefits that reflect the client's financial profile and needs; maintaining existing relationships – a long-term relationship between the client and the bank can positively affect the overall loyalty of the client; more efficient approval processes - faster and more efficient for previously loaned clients, which can increase client satisfaction and reduce costs; expanding the portfolio – by re-crediting existing clients, the bank can gradually expand its loan portfolio and diversify risk. This variable's odds ratio (OR) is 1.336, meaning that if the client is previously credited, the higher the odds are that he will repay the loan in time.

Average Monthly Inflow to SA, measured in hundreds of EUR, represents the amount regularly paid into the client's SA every month. This information has several benefits for the bank: ensuring the stability of deposits – regular inflow of funds to the SA contributes to the stability of deposits, which is critical to maintaining bank liquidity and stability; potential for additional services – clients with a regular flow of money to their SA may be more inclined to use other products and services of the bank, such as savings, loans, investments or cards, which can provide additional profits to the bank; reducing the risk of overdraft – clients with stable incomes are less likely to face unauthorized overdrafts, which reduces the need for the bank to intervene and charge additional fees; better assessment of credit risk – clients with a stable income usually represent a lower risk for the bank compared to clients whose income varies or is irregular; opportunity for personalization of services; more efficient liquidity management. This variable's OR is 1.015, meaning that the higher the monthly inflow to SA, the higher the odds the client will repay the loan in time. Similarly, annual farm income was a significant factor for small-scale farmers (Isibor and Nkamigbo, 2019).

Average Monthly Number of SA Transactions refers to the total number of financial transactions that the client performs on his SA during the month. Some of the benefits that the bank can have from a high average monthly number of transactions on the SA include: income from fees – the bank may charge fees for certain types of transactions, increasing the bank's income; increased client interaction – more frequent interaction enables the bank to provide additional services, transaction notifications, personalized offers or advice; encouraging the use of digital channels – reducing operational costs compared to traditional methods, contributing to more efficient operations; better understanding of client needs – the bank can adjust its services, offers and marketing strategies; reduced risk of overdraft – clients who regularly transact on their SA often have better control over their finances, reducing the risk of unauthorized transactions or overdrafts; ability to offer personalized products; better risk management - helps the bank identify potential risks, such as suspicious transactions or fraud. However, as opposed to the expectations, this variable's OR is 0.981, meaning that the higher the monthly number of SA transactions, the lower the odds that the client will repay the loan in time.

Profiling in Months refers to the time that has passed since opening the SA. Benefits for the bank include long-term client loyalty, monitoring financial behaviour, increasing proactivity in providing services, target groups, personalizing services and communicating. However, as opposed to the expectations, this variable's OR is 0.625, meaning that the longer the profiling, the lower the odds that the client will repay the loan in time.

Age of the client at the time of applying the bank's product can significantly affect various aspects of the banking relationship: credit risk - younger clients often have longer service life and generate income for a longer time; types of products and services; long-term client relationship; marketing strategies - better targeting different age groups; risk insurance; customized offers. This variable's OR is 0.827, meaning that the older the client, the lower the odds that he will repay the loan in time. The results are in favour of younger clients. Some authors have also found that age negatively affects the repayment rate of smallholder farmers (Kassegn and Endris, 2022).

Mail Availability is important to the bank for personalized communication since they may use e-mail to inform clients about new services, updates, interest rates, policy changes, and other significant information. Clients can receive electronic reports instead of paper statements via e-mail, which is more environmentally friendly and convenient. The bank can send reminders about upcoming payment deadlines, which can help clients avoid delays and unwanted fees. Clients can receive e-mail notifications about changes in laws and regulations that affect banking services or their accounts. However, as opposed to expectations, this variable's OR is 0.767, meaning that if the mail is available, the odds that the client will repay the loan in time are lower.

Loan Type monitoring compares new and previous applications and possible predictions of new loans by maturity and amount. Clients may use three types of loans: working capital, overdraft, or investment. Working capital loans provide short-term funding for operational needs, overdrafts offer flexible borrowing up to a certain limit for immediate expenses, and investment loans are long-term financing for major purchases or projects. Clients benefit by receiving funds to start or expand business or maintain liquidity, while banks benefit by earning income from interest and fees. In addition, loans often have certain conditions that help the bank monitor and manage risks.

Loan Amount, measured in thousands of EUR, provides valuable information about the client. A bank can consider offering long-term loans if the client has demonstrated the ability to maintain financial discipline in the long term. This variable's OR is 1.025, meaning that the higher the loan amount, the higher the odds the client will repay the loan in time. The loan amount was also found significant by Isibor and Nkamigbo (2019).

Employment Status is read from the Excerpt from the register of agricultural holdings and includes (1) exclusively engaged in agriculture, (2) engaged in countryside tourism, (3) agriculture is the predominant activity (more than 50% of working time), (4) pensioner (in case of non-existence of formal status of pensioner, persons over 65 years of age), and (5) agriculture is an additional activity (less than 50% of working time). The data can help make the final loan decision correctly and with the rating. Clients who are exclusively engaged in agriculture, engaged in countryside tourism, or have agriculture as the predominant activity (more than 50% of working time) are considered more desirable when assessing the rating. On the other hand, pensioners or clients for whom agriculture is an additional activity have additional income other than agriculture. Their taxes are settled from other incomes (no tax debt), so they are more acceptable from the point of view of risk.

Owned Farm Area is also read from the Excerpt from the register of agricultural holdings. This variable's OR is 0.986, meaning that the larger the farm area, the lower the odds that the client will repay the loan in time. The results favour smaller farms, as opposed to some findings that land size positively influences the repayment rate of smallholder farmers (Kassegn and Endris, 2022).

Farm Holder's Age When Applying is a significant factor when assessing the creditworthiness and general risk for the bank. Younger smallholders without financial history present a challenge in evaluating creditworthiness. Older smallholders often have a more stable financial situation, long-term work experience, and more experience in business but may be closer to retirement. This variable's OR is 1.220, meaning that the older the client is when applying for a loan, the higher the odds he will repay the loan in time. As opposed to the total age, this result favours older clients at the time of application. This result is in accordance with the previous literature studies. We showed that it is more probable for older farmers at the time of application to repay the loan in time. Like-

ly, Das and Sharma found that the over-indebtedness is related to the farmers from a lower age group (Das and Sharma, 2023).

Clean Credit History is read from the CB report and is generally one of the parameters of the loan rating. The bank usually analyzes this information to make an informed decision and manage risks per policy and objectives. Suppose the client has regularly met his financial obligations in the past and has no late payments. In that case, this usually positively affects his credit rating and relaxes the terms of loan approval by the risk. A clean credit history without historical delay is essential when evaluating a client's credit rating. Positive impacts include: bank's trust – the bank usually evaluates repayment history to assess the level of risk associated with granting a loan; increase in credit rating – regular settlement of obligations usually results in an improvement in credit rating, which can lead to more favourable loan terms; more favourable loan terms; faster approval process; lower risk of non-payment – clients with a good credit score and a clean repayment history represent a lower risk for the bank in terms of potential unpaid debt; beneficial impact on the bank's portfolio. As expected, this variable's OR is 1.862, meaning that if the client has a clean credit history, the odds are higher that he will repay the loan in time.

Past Due Records over 5 Days are read from the CB report. If the smallholder has a recorded past delay in the CB for more than five days, this can significantly impact the bank's risk assessment and approval of the loan. It can serve as an indicator of financial problems and increased risk. These clients are categorically considered different from clients with a clean credit history. They are often asked for additional collateral or evidence to reduce the potential risk of a possible delay in repayment of the new loan. The bank can more carefully analyze their financial ability to meet obligations before approving a new loan. Interest rates could even be increased to compensate for increased approval risk and stricter lending conditions. As expected, this variable's OR is 0.459, meaning that if the client has past due records over five days, the lower the odds that he will repay the loan in time.

No Credit in Past is read from the CB report.

The absence of earlier data on credit behaviour can affect the client's rating through a lack of data for analysis, increased uncertainty, or difficulty in determining creditworthiness. Possible impacts on ratings include a lower initial rating category, gradual rating increase, and additional requirements or collection of alternative evidence. However, this variable's OR is 1.306, meaning that if the client had no credit in the past, the odds that he will repay the loan in time are higher.

Years Between First Product Approval and Report is read from the system, which counts the years from the approval of the first placement until today. It provides a complete picture of the client: he used/did not use the bank's products, was late/regular in repayment, and sufficient information for the risk parameter in which this is contained. Potential benefits include: long-term loyalty – if a long period has passed from the approval of the first product to the date of the report, this may indicate a long-term relationship with the bank and client loyalty; insight into loan repayment history; product resale – a long period may indicate the need to re-engage the client and resell the product; personalized offers; more efficient loan approvals. This variable's OR is 282, meaning that the longer the time between the first product approval and report, the higher the odds that the client will repay the loan in time.

Tax Debt Status, measured in thousands of EUR, is read from a tax certificate the client must provide. The client is registered to pay taxes from agriculture if the basis of the work activity is only agriculture or rural tourism. Tax debt in some parts of Serbia is present; some farmers owe 10-20,000 EUR with interest. The state has not resolved this yet. High debts of 10-20,000 EUR with interest can significantly burden the financial situation of farmers. It impacts liquidity, creating a need for tax solutions and government actions. This variable's OR is 0.954, meaning that the higher the debt status, the lower the odds that the client will repay the loan in time.

Livestock is read from Excerpt from the register of agricultural holdings (cattle, sheep, pigs, etc.). Clients who have more livestock are better rated. Livestock includes dairy cows and bulls, sows and fattening pigs, sheep, goats, etc. Calculation of creditworthiness for a working

Table 3 - Comparison of machine learning algorithms performance.

Model	F1	Accuracy	ROC AUC	Timely repayment	Confusion matrix	
					Yes	No
XGBoost	92.78%	92.28%	92.23%	Yes	92.98%	7.02%
				No	8.53%	91.47%
Random forests	65.37%	61.14%	60.79%	Yes	68.6%	31.4%
				No	47.02%	52.98%

capital loan implies indebtedness concerning production costs. In the case of an investment loan, the instalment and annual repayment are calculated based on the net profit. However, this variable's OR is 0.998, meaning that the more livestock, the odds that the client will repay the loan in time are lower. This result is opposed to the findings of Kassegn and Endris (2022), who showed that livestock has a significant positive influence on the repayment rate of smallholder farmers.

The second part of our research includes applying and comparing specific machine learning algorithms to find the model that best predicts the data. As discussed before, our output was a binary variable, namely, a *timely repayment* that denotes whether the bank client - a smallholder – repaid his loan on time. Based on the previous literature, we have chosen three models that showed the best results: Random Forests, SVM, and XGBoost. The SVM model gave very low accuracy prediction results when modelling timely credit repayment; thus, we have focused on XGBoost and Random Forests. We have divided the dataset into train and test sets encompassing 70% and 30% of the dataset. We have compared the performance of these machine learning algorithms. The results are given in Table 3.

As can be seen from Table 3, the Random forests model provided even lower accuracy than the Logit model. Thus, we have further analyzed only the XGBoost model. XGBoost has predicted timely loan repayment with more than 92% accuracy. Area Under Curve (ROC AUC), an aggregate performance measure across all possible classification thresholds, is 92.23%, indicating that the model can discriminate between the two classes. XGBoost model is likely to be reliable in its predictions. An F1 score for the model is 92.78%, indicating a solid balance between precision and recall and suggesting a robust model performance.

In Figure 1, we have shown Shapley's additive explanations (SHAPS) of the XGBoost model (Nohara *et al*., 2022; Shi *et al*., 2022; Wieland *et al*., 2021) to find which of the input variables are most important for predicting timely credit repayment.

From Figure 1, the most critical factors determining timely repayment are Clean Credit History, Average Monthly Inflow to SA, Period of Owning SA, Farm Holder's Age When Applying, and Horticulture. As in the Logit model, if the client has a clean credit history, the chances are higher for the timely repayment of a loan, as evident from Figure 1. A higher average monthly inflow to SA increases the chances of repaying the loan in time. Also, as in the Logit model, if the client is older when applying for the loan, the chances to repay the loan in time are higher.

Interestingly, two variables were found to be important for prediction in XGBoost but were not significant in the final Logit model: Period of Owning SA and Horticulture. Besides timely repayment, the *Period of Owning SA* benefits the bank through long-term client loyalty and monitoring financial behaviour, enabling personalized offers and adaptive services. *Horticulture* is read from the Excerpt from the register of agricultural holdings and then distributed within the system by categories and types of products to calculate the client's creditworthiness. Calculation of creditworthiness for a working capital loan implies indebtedness concerning production costs. For example, in an investment loan, the annual repayment is related to the net profit from horticulture.

Figure 1 - XGBoost SHAPS.
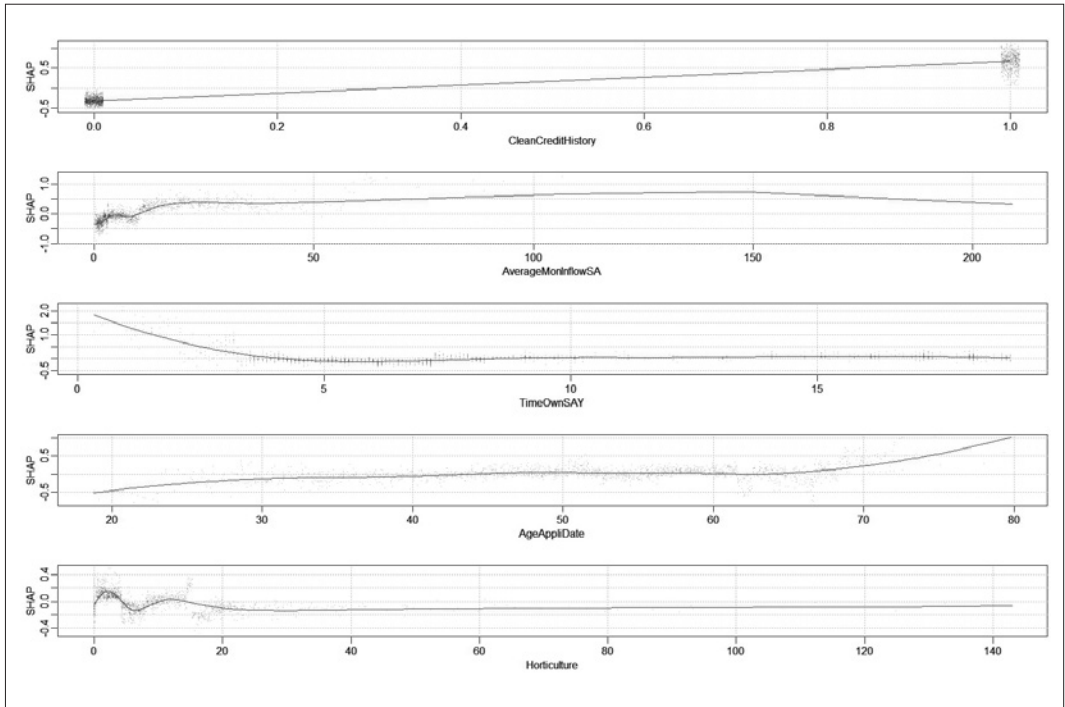
Source: Produced by the author.

5. Conclusion and Policy Implications

Financial institutions in developing countries continue to grapple with the critical issue of defaults on borrowed funds, which poses a significant challenge in their efforts to broaden their services and reach a wider client base (Kassegn and Endris, 2022). This issue is closely tied to the need to improve credit literacy, enhance land productivity, diversify income sources beyond agriculture, and simplify standard credit procedures for marginal farmers and landless sharecroppers, as Das and Sharma (2023) suggested. The lack of access to financial services, particularly loans, is a critical factor in the poverty and underdevelopment of smallholder farmers. While in Serbia, only 10% of smallholder farmers use loans, in Turkey, for example, agricultural land accounts for a significant portion of the total capital, and surveys show that 78% of agricultural enterprises use agricultural loans and spend 88% of them for input purchases (Kusek *et al*., 2017). The low profit rate and the emerging individual needs increase these loan demands. The credit policy of Serbian banks is providing cheap or free loans, or 30-50% cash back for investments and WC in agriculture. The credit policy of agricultural credit cooperatives and agricultural banks in Turkey is to apply subsidies of 50% (like for livestock) to 100% (like for irrigation investments) of loan interest rates (Kusek *et al*., 2017). The same authors state that many modern agricultural enterprises have been established thanks to the projects supported by the EU and the Ministry of Agriculture, which are also the main credit supporters in Serbia.

Nevertheless, banks are deeply concerned about the high rate of loan defaults. Given these interconnected challenges, our study is dedicated to identifying the factors that contribute to the timely repayment of loans, aiming to address both the needs of the financial institutions and the borrowers effectively.

The first part of our study presents the econometric results obtained to determine the significant influence factors. Striving towards establishing and clarifying relations between independent

variables and timely loan repayment of smallholder farmers in Serbia, we developed a Logit model that provided about 64% accuracy. The model discovered 18 significant predictors out of 36 initial feasible determinants. The significant and positive influence of the variable previously credited clients indicates that pre-lending to clients can bring multiple benefits to the bank. Besides timely loan repayment, these are higher revenues, more efficient processes, and maintaining long-term client relationships. In the case of a new client, the approval process is based on available external data and risk cost based on the existing portfolio of similar client groups. The regular average monthly inflow to SA brings banks stability through timely loan repayment, as well as the opportunity to increase income and provide additional services to clients, contributing to maintaining the successful operation of the bank. Besides affecting timely repayment, a clean credit history positively affects the client's rating and allows him favourable conditions when applying for a loan. No credits in the past against the odds positively influence timely repayment. Still, it is important to understand that the absence of a previous credit history does not automatically mean an unfavourable rating. The bank will carefully analyze all available information and use alternative indicators to make an informed decision about the client's risk and rating. Regularly settling new obligations can gradually improve the client's rating over time.

The findings of our study revealed that the historical delay in CB – over five days, negatively influenced the timely loan repayment. In essence, it can significantly affect the risk assessment and conditions for approving a new loan for an agricultural holding. Banks will make loan approval decisions based on their risk management policies and practices, considering this relevant information from credit reports. Another negative influence was found with tax debt status. Cooperation between farmers, local authorities, and the state can be crucial to solve such problems effectively. In addition, providing support to farmers through education on tax obligations and proper planning can contribute to the long-term resolution of these challenges.

As opposed to expectations, our study shows that the average monthly number of SA transactions negatively affects timely repayment, even if it brings numerous benefits to the bank, including additional revenue, better understanding of clients, increased efficiency, and opportunities for personalization of services. A similar situation is for profiling in months, which provides the context for better understanding and adjusting the approach to build a long-term and mutually beneficial relationship with the client.

The client's age significantly impacts the bank's approach and strategy, and tailoring services and benefits can contribute to better client satisfaction and the bank's long-term success. Our results favour younger clients, following the findings of other authors (Kassegn and Endris, 2022). On the counter, age when applying for a loan favoured older clients. When analyzing the creditworthiness, the bank will carefully consider the age of the smallholder, taking into account all relevant factors that affect the viability of the business and the ability to meet obligations according to the agreed terms of the loan.

Some of our findings differ from the literature. For example, in our study, the number of farm members or education was not shown to influence the timely repayment of agricultural loans. At the same time, some authors found that family size and education level were significant factors (Kassegn and Endris, 2022).

The second part of our study enhances model accuracy using machine learning algorithms. XGBoost model has shown the best performance among the tested models, providing 92% accuracy. Using the SHAPS of the XGBoost model, we identified the most critical factors determining timely repayment: clean credit history, average monthly inflow to SA, period of owning SA, age when applying for a loan, and horticulture. Clean credit history, inflow, and age at the moment of application coincided with the Logit model results. Still, the XGBoost model identified two additional significant predictors: the period of owning SA and horticulture.

This paper aims to present how existing data can be used more precisely and efficiently so that banks increase the accuracy of the assessment in the approval process. Using digital tools and

data should have a double-sided positive effect. First is on the banks, a faster and cheaper process with fewer default clients. The second is on the customers, giving them faster approval times and access to funds. In general, improvement like this should also positively affect a loan price because, according to Basel II, the projected loss must be calculated in loan price like a "risk cost". If we have a lower percentage of defaults, risk cost will be decreased, and the end price – total interest rate – will be lower.

The findings of this study have several important policy implications for financial institutions and policymakers in developing countries. Firstly, the importance of a clean credit history, regular income, and specific agricultural practices like horticulture as significant factors in loan repayment suggests that banks should refine their credit assessment processes to include these variables more prominently. This could lead to more accurate risk assessments and potentially lower default rates. Secondly, the study highlights the need for financial education among smallholder farmers, particularly in managing credit and understanding tax obligations, which could be achieved through collaborations between banks, local authorities, and agricultural organizations. The findings also suggest that banks should consider the age and agricultural experience when evaluating loan applications, as these factors were shown to influence repayment. Additionally, using advanced machine learning models like XGBoost in credit scoring indicates a shift towards more sophisticated, data-driven decision-making processes in the agricultural finance sector. This could improve the accuracy of banks' analyses and help banks tailor their services more effectively to the needs of individual farmers.

Improving and extending agriculture financing remains a significant challenge and top priority for policymakers (Bharti, 2018). For a few decades, the determination of creditworthiness for small individual farmers did not improve. The most often used tool in the worldwide market is the traditional method of credit capacity determination, established in micro-credit organizations many years ago. Future directions for our research might include assessing the factors influencing loan approval. Given that the agricultural loans are specific in terms of quantity and scope of data required from smallholder farmers, we are also attentive to improving and expanding the existing methodology for loan approval, which is currently in banks.

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