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The Impact of the COVID-19 Pandemic on the Saudi Credit Industry: An Empirical Analysis Using Machine Learning Techniques to Focus on the Factors Affecting Consumer Credit Scoring

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Abstract

The main purpose of this study is to investigate the impact of the COVID-19 pandemic on the Saudi consumer credit scoring by implementing a variety of machine learning techniques. To evaluate the magnitude of this impact, we used 10 data sets of 1,000 clients randomly extracted from several banks operating in Saudi Arabia under the supervision of the Saudi Central Bank (SAMA). This study spans two years before the pandemic (2018 and 2019) and the pandemic year itself (2020). The empirical findings of the WEKA decision tree (J48 algorithm) indicate that before the pandemic, the essential qualities of credit applicants were related to their personal status and the purpose of obtaining a loan. However, after the pandemic, the applicants' characteristics were highly influenced by their job type.

Keywords: Credit scoring, credit segmentation, behavioural scoring, data collection, machine learning

JEL Classification Code: C1; C6; C8; G4; G2; O1

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1. Introduction

Generally, financial and banking services are among the oldest services in the Gulf region for many reasons. For example, during the Hajj and Umrah seasons, many pilgrims visit Saudi Arabia to practice their faith and prayers. This large number of people coming from different parts of the world and holding different currencies resulted in the presence of a small number of foreign financial institutions and Saudi money exchangers during the early 20th century (Oxford Business Group, 2021).

However, over the past few years, the banking sector in the kingdom has faced several challenges. For example, in late 2014, the oil prices significantly dropped, increasing the pressure on the financial sector in the kingdom. In addition, the essential budgetary changes and reforms that followed such a drop in oil prices raised concerns regarding growth opportunities (Oxford Business Group, 2021). In 2015, this decline in oil prices decreased the aggregate asset growth to a low of 3.4%, which further decreased to 0.4% in 2017. However, in 2018, an improvement in oil prices was observed as a result of the cooperation between Saudi Arabia and other major OPEC and non-OPEC oil producers in the OPEC+ agreement and the adoption of new approaches involving expansion plans and reductions in energy subsidies. By 2019, the continued stabilisation of oil prices, combined with the kingdom's development strategy through the objectives and programs of the Saudi Vision 2030 framework, overseen by His Royal Highness Crown Prince Mohammed bin Salman, helped accelerate the development and improvement of all life sectors, resulting in a more positive impact on the Saudi economy.

According to SAMA's 57th annual report in 2020, the Saudi banking sector has remained resilient and stable during the COVID-19 pandemic all thanks to the procedures and measures taken collectively by SAMA and Saudi banks. Such efforts have played a major role in mitigating the potential adverse impacts of the COVID-19 pandemic on the private sector in general and the banking sector in particular. Such positive results can be observed through financial soundness indicators, such as the increase in the capital adequacy ratio to 20.3%, exceeding the international requirements of the Basel Committee on Banking Supervision, and the increase in the assets and deposits of banks by 13.2% and 8.2%, respectively.

In recent years, credit has represented a high-growth segment in Saudi Arabia and a key driver behind sector growth. Generally speaking, credit growth in Saudi Arabia has been previously studied. It has also been documented that bank lending is affected by bank balance sheet conditions, macroeconomic developments, and supply-and-demand factors (Miyajima, 2017). According to the Saudi Hollandi Capital report (2011), four factors influence banking growth: current economic growth, demographic pattern, private sector growth, and increased fiscal capital expenditures.

Credit risk has an important place in the financial literature. In general, most of the banks worldwide prioritise managing credit risks, including in Saudi Arabia. As mentioned, earlier, Saudi Arabia has one of the first banking structures in the Middle East (KPMG, 2020). Even before the pandemic, the kingdom's banking industry demonstrated promising profit growth in 2019. Hence, the Saudi banking sector is considered an essential and flourishing sector in the kingdom's economy. However, with the emergence of the COVID-19 pandemic in early 2020, the global banking industry, including the Saudi banking sector, faced significant challenges.

During this period, SAMA provided support for domestic banks by providing several essential stimulus measures to mitigate or even eliminate the effects of COVID-19 on the Saudi private sector. These stimulus measures included, but were not limited to, supporting bank customers who have lost their jobs, restructuring loans without additional fees, and waiving charges for accounts holding below-minimum balances (KPMG, 2020).

Moreover, to provide all the necessary credit information for risk analysis and borrowers' creditworthiness evaluation, the Saudi Credit Bureau (SIMAH) proposed many products and services, such as the SIMATI retail system and the SIMAT corporate system. As mentioned in SAMA's 57th annual report, the total credit reports issued by SIMATI for the retail sector dropped by 36.7% to 12.3 million during 2020 from 19.5 million in 2019 because of the repercussions of the COVID-19 pandemic. Conversely, the total credit reports issued by SIMAT for the Saudi market witnessed a notable increase of 19.8% to 81.0 thousand during 2020 from 67.6 thousand in 2019. In addition, the total credit accounts in SIMAT increased by 2.9% to 1.802 million during 2020 from 1.751 million in 2019. Moreover, the total number of consumers in the business sector in SIMAT increased by 2% to 798.5 thousand during 2020 from 782.6 thousand in 2019.

However, despite all the efforts made by SAMA, the long-standing effects of the pandemic on credit scoring in Saudi Arabia and worldwide remain fuzzy. In general, there are two types of credit scoring: application scoring and behavioural scoring (Baesens, 2017).

On the one hand, the purpose of application scoring is to reach a credit score that can predict the risk of defaulting of a credit applicant at the moment of the loan application. On the other hand, the purpose of behavioural scoring is to develop a statistical credit scoring model that can analyse the behaviour of already acquired credit customers (Baesens, 2017). Thus, behavioural scores can be used for various business purposes. However, most of these models were built on historical data from the last decade and, hence, are not representative of the current COVID-19 situation. Therefore, in this paper, we propose studying the various policies implemented by the Saudi government to face the inherent attributes of COVID-19. Next, we investigate how credit scoring and behavioural scoring can help segment different defaulting credit applicants before and during the COVID-19 pandemic. We use a combination of unsupervised and supervised learning to divide unworthy applicants into different groups and then target each segment individually.

This paper is organised as follows. Section 2 describes works related to credit scoring and behaviour scorecards. Section 3 illustrates the Saudi government’s approach to curb the effects of the COVID-19 pandemic and its economic impact. Section 4 introduces the proposed approach to identify credit risk on the basis of a cluster analysis of account behaviours. Section 5 presents the empirical framework and data collection method. Section 6 presents the empirical results of clustering combined with a decision tree model. Finally, Section 7 outlines the research conclusions.

2. Literature Review

Credit scoring relies on the evaluation of risks related to lending money. According to Bouaguel et al. (2014) histories of past lending and repaying transactions are collected and evaluated by lenders in order to assess the will to repay loans and help credits managers to take decisions (Hand and Henley, 1997). The probability of an applicant defaulting should be estimated from the applicant's information at the time of securing a loan. This estimate then serves as the basis for an acceptance or rejection decision. New sophisticated models for deciding whether to grant credits or not are now available. These models are based on the emergence of new machine learning technology and replying the traditional methods that relies on human judgment.

According to Baesens (2017), there are two types of credit scoring: application scoring and behavioural scoring. Application scoring models, known as scorecards or classifiers, use information from application forms and other sources to estimate the probabilities of defaulting (Bouaguel et al, 2014). Then, deciding to grant a credit will depend on the estimated likelihood of defaulting, which will be compared to a suitable threshold. Thomas (2009) showed that the prediction accuracy of standard statistical methods for developing scorecards such as discriminant analysis or linear regression is erroneous in some specific cases, despite their simplicity. Hence, other models based on data-mining methods have been proposed. These models, however, do not yield scorecards, but they directly indicate the credit applicant's class (Jiang, 2009).

In the behavioural scoring credit model, decisions are based on how to deal with already existing customers (Thomas, 2000). This type of model analyses the credit limits of the current borrowers and identifies whether a financial institution should approve an increase or a decrease in their loan limit. Moreover, it can sometimes predict and propose the type of measure or action that needs to be taken.

Many researchers focussed on behavioural scoring, such as Chen et al. (2009) and Ifei and Chen (2011), who proposed a particular behavioural scoring model that classify customers into high or low contribution customers based on data envelopment analysis. Other researchers, such as Thomas (2000) and Hsieh et al. (2010), studied how to build behavioural scorecards with machine learning components. They presented a complete survey of credit and behavioural scoring related to forecasting the financial risks of lending consumers.

3. Saudi Government's Approach to Curb the Effects of the COVID-19 Pandemic and Its Economic Impact

After recording the first COVID-19 case on March 2, 2020, the Saudi government and Saudi Central Bank took a proactive approach and provided a set of support packages and stimulus measures targeting various economic sectors with issues related to financing, employment, tax payment deferrals, and a moratorium on debt repayments. These packages included, but were not limited to, the exemptions and postponement of some government dues totalling more than SAR 70 billion, a package of more than SAR 125 billion to support the banking and payment system alongside financing support for small and medium-sized enterprises (SMEs), the injection of SAR 50 billion into the banking system to enhance liquidity and allow banks to continue providing credit facilities for the private sector, the allocation of SAR 50 billion to ensure that the government dues to the private sector are met on schedule, and a 60% wage subsidy for Saudis working in the private sector (MOF, 2020; KPMG, 2020; SAMA, 2020).

3.1 Employment-related measures

During the pandemic, the Saudi government declared that it would pay around 60% of the salaries of Saudi employees employed in the private sector for three months with a maximum amount of SAR 9 billion. Moreover, also during the pandemic, the Human Resources Development Fund allocated around SAR 5.3 billion to support firms in private sector in hiring and training unemployed Saudi citizens. In addition, several employment-related initiatives and measures, such as suspending fines related to expat recruitment, lifting any suspensions related to wage protection during the pandemic, and facilitating the return of expatriate employees to their homelands, among many other measures, were taken to alleviate the impact of the pandemic on the private sector (KPMG, 2020).

3.2 SAMA's measures and financial support programs

SAMA through a set of different financial measures continues to allow the banking system to support the private sector. This comes as part of supporting the efforts made by the Saudi government to alleviate the anticipated financial and economic impacts of the pandemic on the private sector, especially on SMEs. In fact, after the first case of COVID-19 was reported in Saudi Arabia, SAMA announced in March 2020 the introduction of a private-sector financing program consisting of four main initiatives. These initiatives are a Deferred Payments Program, which has been extended three times; a Guaranteed Facility Program, a Loan Guarantee Program; and a Point of Sales and E-Commerce Service Fee Support Program which are operating on a budget of more than SAR 125 billion. As well as liquidity injection of SAR 50 billion by SAMA to support banking system. These programs aim to mitigate the impacts of the precautionary measures on the micro, small, and medium enterprise sector by reducing the burden generated from cash flow fluctuations, backing up the sector's working capital process, and enabling and maintaining its growth and level of employment during the ensuing period of the pandemic (SAMA, 2020).

3.3 Fiscal and tax measures

In March 2020, right after recording the first case of COVID-19 in the kingdom, the Saudi government assessed the situation and implemented immediate precautionary and robust measures to ensure the safety of its citizens and residents. To mitigate the pandemic's financial and economic impact and provide support to the private sector during such hard times, the government prepared and introduced a set of urgent fiscal initiatives. Among these initiatives, the financial stimulus package reached more than SAR 70 billion, including exemptions related to expat levies and the postponement of some government dues and taxes to provide liquidity to the private sector. This allowed businesses across each industry to manage the continuity of their economic activities. Moreover, in terms of government spending, the government confirmed its intention to pay its obligations and dues to the private sector in a timely manner (MOF, 2020).

4. Identification of Credit Risk on the Basis of a Cluster Analysis of Account Behaviours

In general, studying the risk levels for defaulting credit accounts is essential for banks to implement the right policies at the right time. Hence, behavioural credit scorecards can be used for this purpose. These types of models can be defined as statistical models of customer behaviour. The aim of these models is to identify which of the existing customers may experience difficulty in paying back their loans (Thomas, 2000). Identifying different risk levels might support choosing the right decisions and decreasing the number of defaulting loans. The idea is to use a cluster analysis of defaulting credit applicants. Cluster analysis is used to assign credit accounts to several groups such that the behaviours of applicants in the same group are similar. This cluster analysis can be used to build different robust behavioural scorecards.

In general, there are many clustering methods in the literature. These methods are commonly classified into the following categories (Han and Kamber, 2000): hierarchical methods, partitional methods, density-based methods, and grid-based methods. Generally, *k*-means clustering is considered one of the well-known unsupervised machine learning algorithms that belong to partitional clustering methods. In this category, we attempt to decompose the data set into a set of k disjoint clusters. Then, we iteratively optimise a criterion function to emphasise the global structure of the data by moving observations from one cluster to another.

It is important to shed light on clustering by merging supervised and unsupervised learning techniques. Hence, K-means method can be used by financial institutions for segmenting their customers and to develop marketing strategies for each segment. The decision trees (DT) method could be merged with K-means method to produce meaningful rules governing the hidden relationships of a dataset and to mine the characteristics of each customer segment. Hence, we will try in the following to analyse consumer credit scoring before and during the pandemic by mixing data mining techniques to analyse customer solvability.

At a first step, the K-means method is used to segment customers based on their solvability level: high, middle and low. Therefore, we first cluster unlabelled data with the *k*-means method. We apply the *k*-means clustering method with $k = 3$ clusters. We select this number considering reasonable objective clustering of defaulting credit accounts. It should be noted, however, that finding the optimal number of clusters is beyond the scope of this research. We first start the process by assigning a label to each sample, making it a supervised learning task.

DT is then used to study the characteristics of each customer segment. DT consists of three principal elements: a root node, an edge, and a leaf node. The root represents the test condition for different features, the edge contains all the possible results that can be present in the test, and the leaf node contains the label of the class to which it belongs. After building a DT model, we inspect the DT's output to quantitatively highlight the characteristics of the clusters. Different strategies could be developed for each customer segments. Using principal component analysis (PCA), Figures 1 and 2 show the outcomes of the *k*-means clustering.

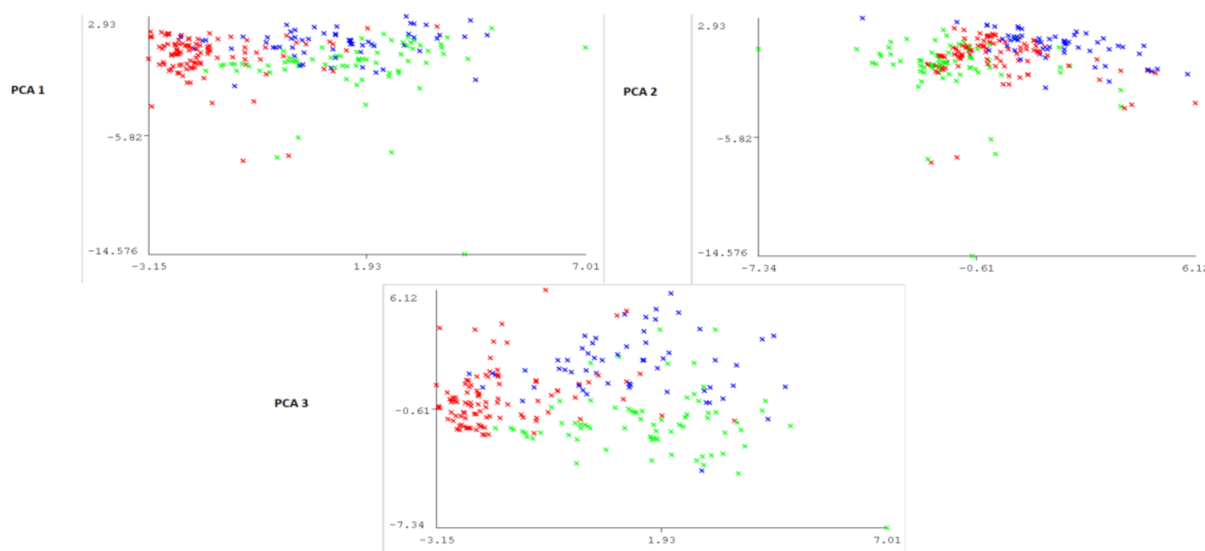

Figure 1 Visual representation of the outcomes of k-means clustering based on the data collected before the pandemic, with principal components.

Both figures show at least three clearly distinguishable clusters, which we have called C0, C1, and C2. Each cluster is associated with a centroid, which is unique to each cluster. The first cluster is shown in red, the second cluster is shown in green, and the third cluster is shown in blue.

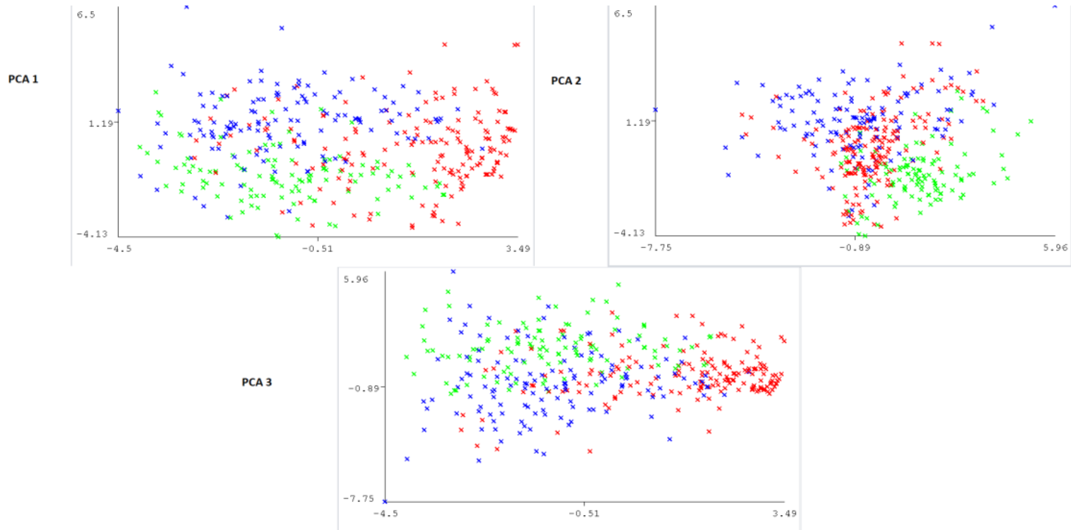

Figure 2 Visual representation of the outcomes of k-means clustering based on the data collected during the pandemic, with principal components.

5. Empirical Framework and Data Collection

5.1 Data set description

To estimate the impact of COVID-19 on the Saudi credit industry, more specifically on the consumer and personal types of loans, we use 10 data sets of 1,000 clients each. All instances were randomly extracted from several banks operating in Saudi Arabia under the supervision of SAMA (for more details, see Table 1). The study period spans two years before the pandemic (2018 and 2019) and the pandemic year itself (2020).

The total number of instances in all data sets is more than 35,000, with about 17 different categorical and numerical features. On the one hand, these categorical features illustrate around 14 qualitative characteristics about each client, such as the region, housing type, personal status, credit history, age, total monthly income, job, loan toner, purpose of personal loan, gender, nationality, number of dependants, and type of collateral with the binary categorical target variable “credit default” (for more details, see Table 1). On the other hand, the numerical features provide information on the client’s total loan amount (including profits) and outstanding credit amount (for more details, see Table 1).

For each data set, missing values are replaced with the average or mode of features depending on the type of the variable (numerical or categorical). Table 2 shows the main characteristics of the data sets used.

Table 1 Description of all features.

Feature	Input	Description
Credit Default	Yes	This specifies whether a borrower defaults to pay back their loan or not.
	No	
Region	Riyadh	This represents the name of the Saudi region where the borrower applies for a loan (mainly based on the classification of the administrative areas in the kingdom).
	Makkah	
	Madinah	
	Qassim	
	Eastern Province	
	Asir	
	Tabuk	
	Hail	
	Northern Borders	
	Jazan	
	Najran	
	Al Bahah	
	Al-Jawf	
Housing Type	Rented	This specifies whether the borrower lives in their owned housing unit or in a rented one.
	Owned	
	Other	
Property Type	Apartment	This specifies the type of housing unit (villa, apartment, etc.).
	Villa	
	Other	
Credit History	No credits were taken before	This describes the record of a borrower’s repayment of past and existing debts.
	All past credits have been paid back duly	

	Existing credits are being paid duly until now	
	There was a delay in paying off in the past	
Age	<25	This classifies the borrowers according to their age profile.
	25–35	
	36–45	
	46–55	
	56–65	
	>65	
Total Monthly Income	<5K	This classifies the borrowers according to their income profile.
	5K–10K	
	11K–15K	
	16K–20K	
	21K–25K	
	>25K	
Job	Government	This classifies the borrowers according to their employer segment.
	Private	
	Retired	
Loan Toner	<12 months	This classifies the borrowers according to the loan duration in months.
	13–24 months	
	25–36 months	
	37–48 months	
	49–60 months	
	>60 months	
Purpose of Personal Loan	Renovation & home improvement	This classifies the borrowers according to the purpose of the loan application.
	Cars & automobiles financing	
	Furniture & consumer durables and goods	

	Education	
	Health care	
	Travel & tourism	
	Other personal loans	
Gender	Male	This classifies the borrowers according to their gender.
	Female	
Personal Status	Divorced	This classifies the borrowers according to their personal status.
	Married	
	Widowed	
	Single	
	Other	
Nationality	Saudi	This indicates whether the borrower is a Saudi citizen or a foreign worker.
	Non-Saudi	
Number of Dependants	0	This specifies the number of family members that the borrower supports.
	1	
	2–4	
	5–9	
	≥10	
Type of Collateral	None	This classifies the borrowers according to the type of collateral.
	Salary transfers	
	Cash collateral	
	Other	
Total Loan Amount (Including Profits)	Numeric	This is a numeric value that describes the total size of the loan granted, including profits.

Outstanding Credit Amount	Numeric	This is a numeric value that describes the outstanding loan value.

Table 2: Summary of the data sets used in the experiments.

<table>
<tr><th>Bank Name</th><th>Number of Instances per Year</th><th>Total Number of Instances</th><th>Missing Value</th><th>No Total</th><th>Yes Total</th><th>Number of Classes</th><th>Number of Categorical Features</th><th>Number of Numerical Features</th><th>Total Number of Features</th></tr>
<tr><td>Al Rajhi Bank</td><td>1,000</td><td>3,000</td><td rowspan="12">Yes</td><td>2,973</td><td>27</td><td rowspan="12">2</td><td rowspan="12">14</td><td rowspan="12">2</td><td rowspan="12">17</td></tr>
<tr><td>Alinma Bank</td><td>1,000</td><td>3,000</td><td>2,983</td><td>17</td></tr>
<tr><td>Arab National Bank</td><td>1,000</td><td>3,000</td><td>2,942</td><td>58</td></tr>
<tr><td>Bank Albilad</td><td>1,000</td><td>3,000</td><td>2,996</td><td>4</td></tr>
<tr><td>Bank AlJazira</td><td>1,000</td><td>3,000</td><td>2,676</td><td>324</td></tr>
<tr><td>Banque Saudi Fransi</td><td>1,000</td><td>3,000</td><td>2,951</td><td>49</td></tr>
<tr><td>GIB KSA Meem</td><td>942</td><td>2,826</td><td>2,781</td><td>45</td></tr>
<tr><td>Riyad Bank</td><td>1,000</td><td>3,000</td><td>3,000</td><td>0</td></tr>
<tr><td>SABB</td><td>1,000</td><td>3,000</td><td>2,966</td><td>34</td></tr>
<tr><td>SAIB</td><td>1,000</td><td>3,000</td><td>2,778</td><td>222</td></tr>
<tr><td>SAMBA</td><td>1,000</td><td>3,000</td><td>2,835</td><td>165</td></tr>
<tr><td>Saudi National Bank</td><td>1,000</td><td>3,000</td><td>2,973</td><td>27</td></tr>
</table>

5.2 Univariate analysis

A univariate, descriptive analysis of all the variables of interest is usually the initial stage in data exploration. The aim of a univariate analysis is to define and summarise the data and find the related hidden patterns. Univariate data can be described bar charts, histograms, frequency polygons, and pie charts.

In this study, we use pie charts to study the hidden properties of data. Pie charts are used primarily to comprehend how a group is broken down into smaller pieces. Thus, the whole pie represents 100%, and each slice denotes the relative size of each particular category.

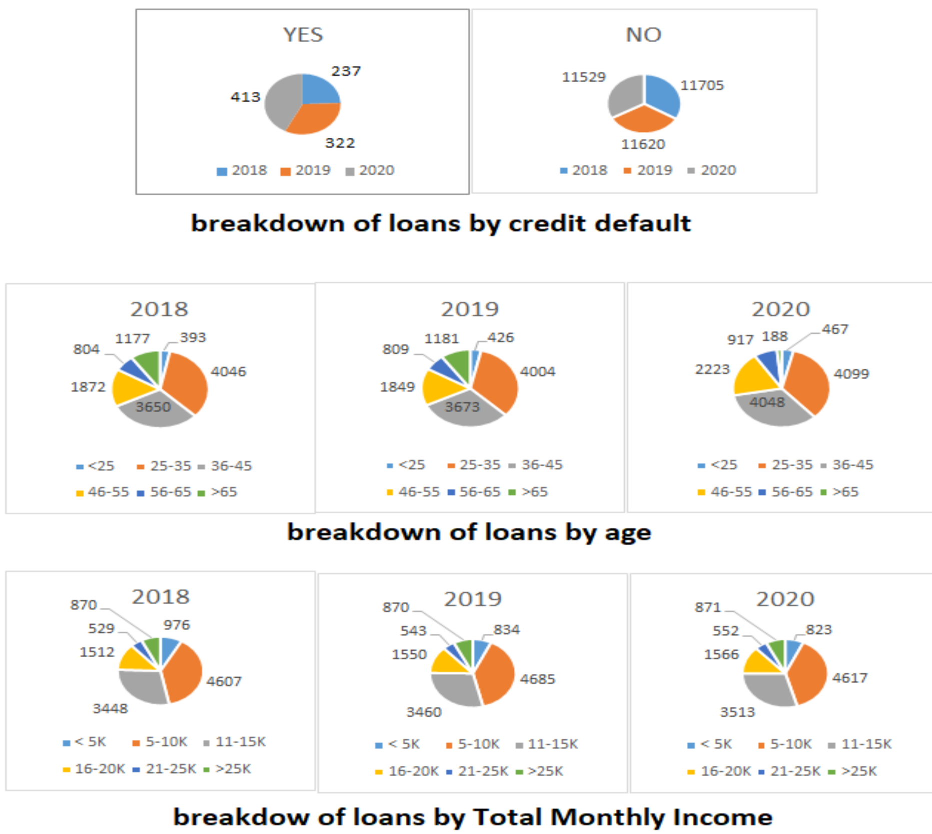

Figure 3: Breakdown of loans by credit default, age, and total monthly income.

The pie charts shown in Figure 3 display the proportions of loans by credit default, age, and total monthly income. It can be observed that the number of awarded credits has decreased a little bit from 2018 to 2020, wherein the number of awarded credits in 2018 with no default was 11,705 and decreased to 11,620 in 2019 and then to 11,529 during the pandemic. It can also be observed in Figure 3 that the number of credits with default has increased during the pandemic. In fact, approximately 45% of the defaulting credit was observed in 2020, the year of the pandemic. One explanation is that during the pandemic, credit consumers shifted to personal loans when they needed cash, making this type of financing one of the fastest-growing forms of debt. However, with millions of Saudi citizens and residents losing their jobs, it became even more difficult to afford monthly payment obligations. Figure 3 shows that borrowers aged between 25 and 35 obtained a significant number of credits. The same was observed for the total monthly income, wherein the largest category of borrowers was those with an income between SAR 5K and SAR 10K. This implies that borrowers aged between 25 and 35 or those with an income between 5K and 10K are the most affected by COVID-19. In general, many reasons exist for why customers aged between 25 and 35 apply for loans. In fact, by this age, many credit customers have spent enough time on the social scene to be able to make an informed decision regarding entering married life. However, with the cost of weddings nowadays being higher than that 10 years ago, financial help during marriage is a given. Most people do not ask for financial help from family and friends and instead take personal loans. For borrowers who have a regular income, taking a personal loan for a wedding and repaying the debt from their salary is a reasonable choice. However, for those who have lost their jobs, it is more difficult to pay monthly payment obligations and usual family expenses.

The pie charts shown in Figure 4 display the proportions of loans by region, loan toner, and the purpose of the loan. It can be noticed that Riyadh exhibits the most significant proportion of credit borrowers, followed by Makkah and the Eastern Province, with the distribution of loans for the remaining areas being very close.

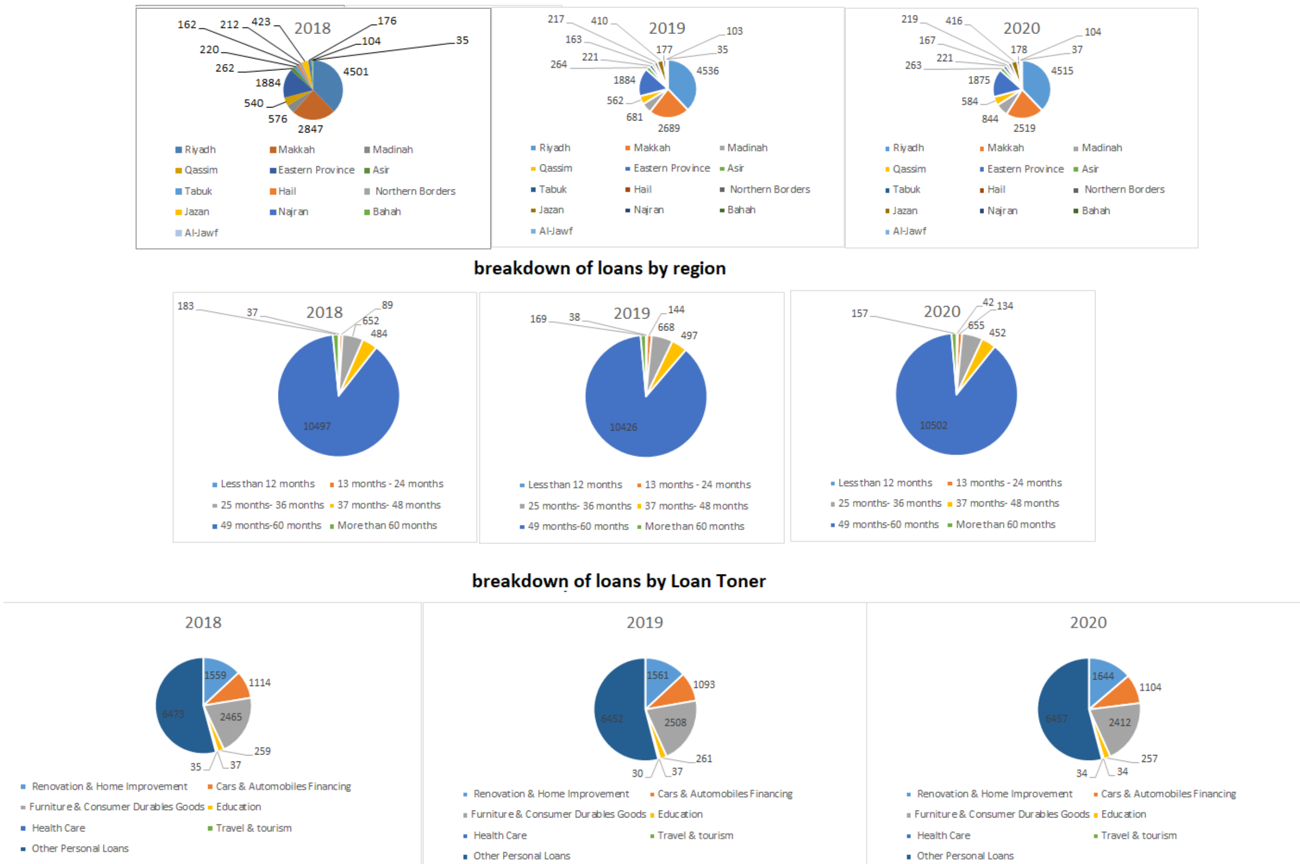

Figure 4: Breakdown of loans by region, loan toner, and purpose of personal loan.

From Figure 4, it can also be noticed that the majority of loans before the COVID-19 pandemic (i.e., 2018) and during the pandemic were taken for a repayment period that varies between 49 and 60 months. In addition, we found that for 2018, approximately 6,437 credits were provided without specifying the exact purpose of the loan.

Figure 5 shows that approximately 85% of the credit applicants in 2018, 2019, and 2020 are males and 15% are females, which means that the credit behaviour related to gender did not change before and during the pandemic. Figure 5 also shows that approximately 90% of the credit applicants before and during the pandemic are Saudi citizens. Moreover, the figure shows that approximately 55% of the credit applicants before and during the pandemic have no dependants under their responsibility and that approximately 35% have two to four dependants under their responsibility. In addition, it can be observed that the majority of the credits applicants before and during the pandemic choose to repay their loans using salary transfers.

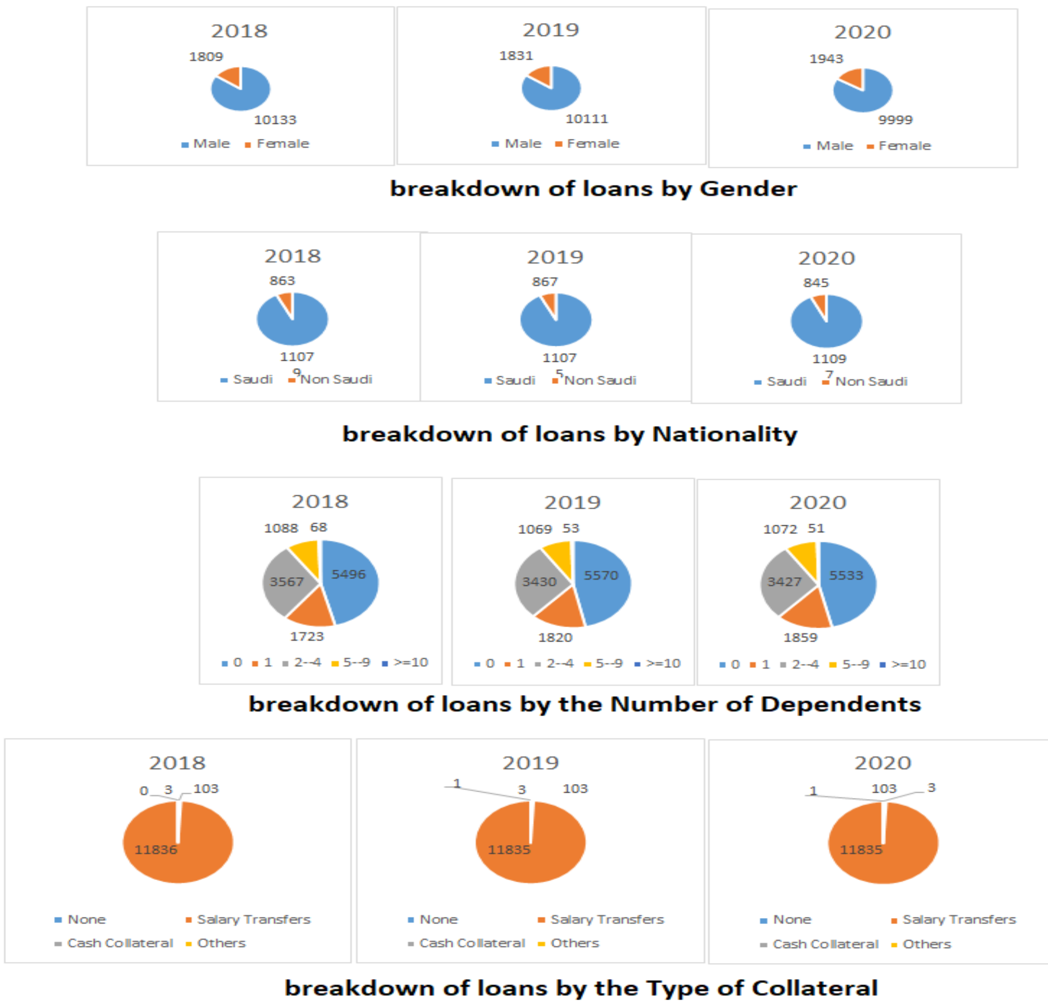

Figure 5: Breakdown of loans by gender, nationality, number of dependants, and type of collateral.

Figure 6 shows that 60% of the credit applicants live in an owned house, 35% live in a rented house, and around 5% live in another type of housing. The figure also shows that approximately 40% of the loan applicants live in villas, 35% live in apartments, and 25% live in another type of property. Moreover, the pie chart of loan breakdown by job shows that the number of applicants from the private sector has decreased from 3,147 in 2018 to 2,552 in 2020, revealing the impact of the COVID-19 pandemic on borrowers from the private sector. The last pie chart in Figure 6 shows that for the period under study, the majority of loan applicants are those with existing credits that are being paid duly until now.

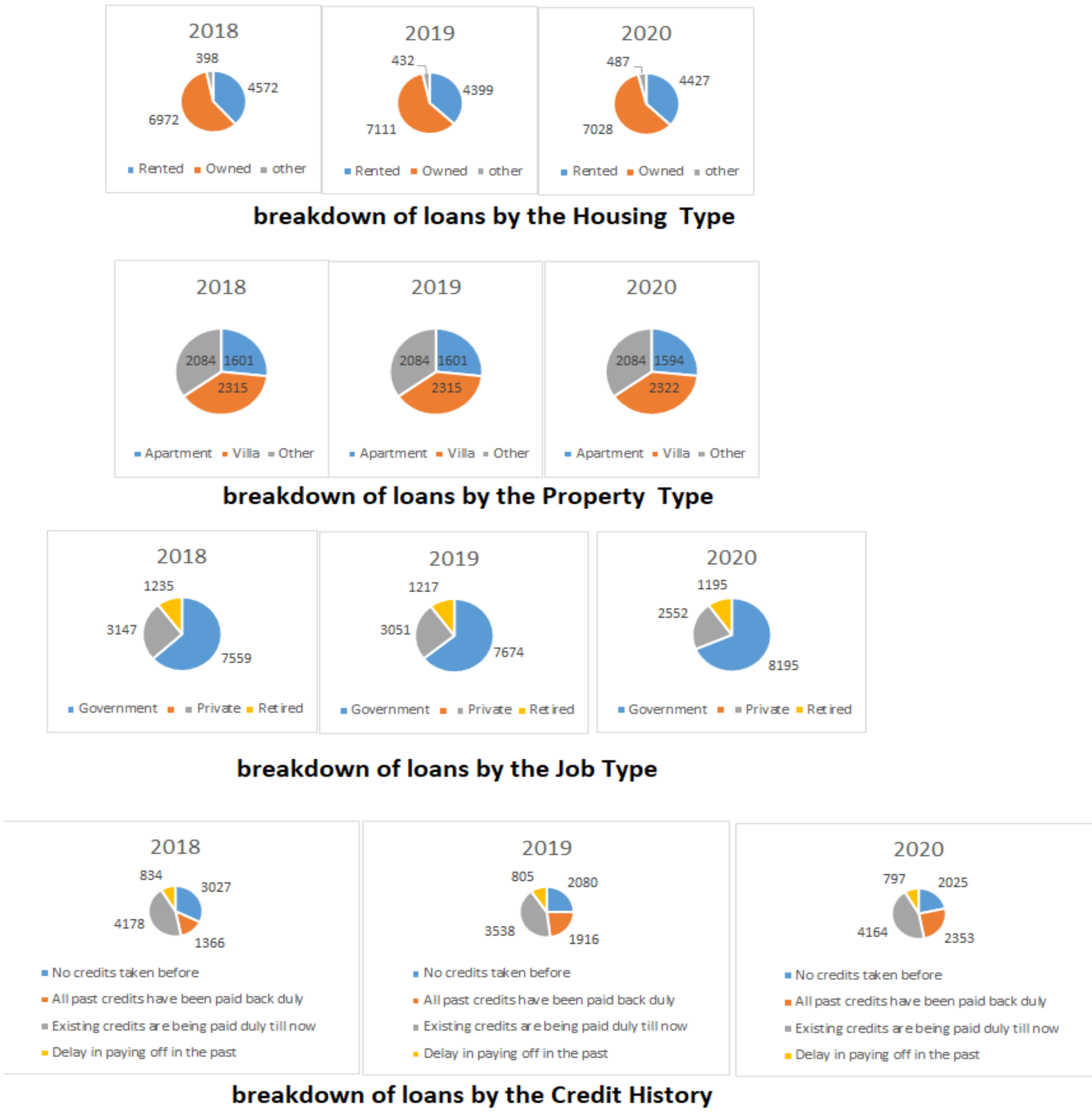

Figure 6: Breakdown of loans by housing type, property type, job type, and credit history.

5.3 Bivariate analysis

In this section, we discuss the results of a bivariate analysis that we performed to find the relationship between each variable in the data set and the target variable "credit default." We use bar charts to attempt to analyse which modality for each feature is related to credit default (see Figures 7 and 8). Bar charts are the most common display of statistical data. These charts help divide categorical data into groups and depict the amounts using bars of various widths. They use either the number of people in each group, also known as the frequency, or the percentage of people in each group, also known as the proportion (called the relative frequency).

Figure 7 helps draw the following conclusions. First, the region of Riyadh ranks first with 45% of noncreditworthy applicants, followed by the regions of Makkah and the Eastern Province. Second, 60% of the defaulting applicants before the pandemic live in owned houses, in most cases villas. Moreover, in most cases, these noncreditworthy borrowers work in the private sector, representing a percentage of 55%. We also found that Saudi citizens have a share of 90% of the defaulting loans compared to 10% for foreign residents over the observation period. In addition, male applicants were found to represent approximately 90% of defaulting credit borrowers, whereas female applicants were found to represent 10% of the total number of defaulting loan borrowers.

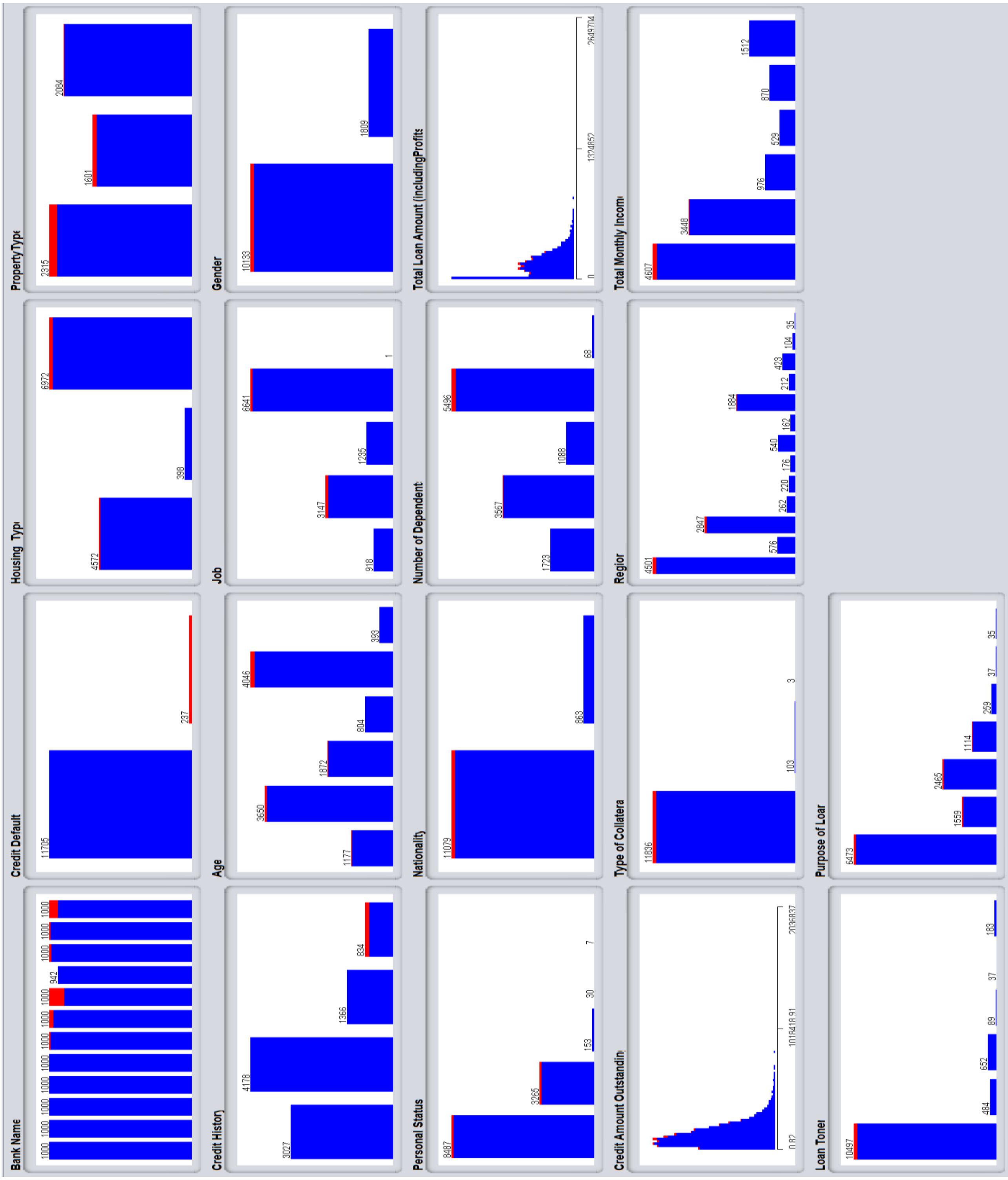

Figure 7 Bivariate analysis for the data before the pandemic.

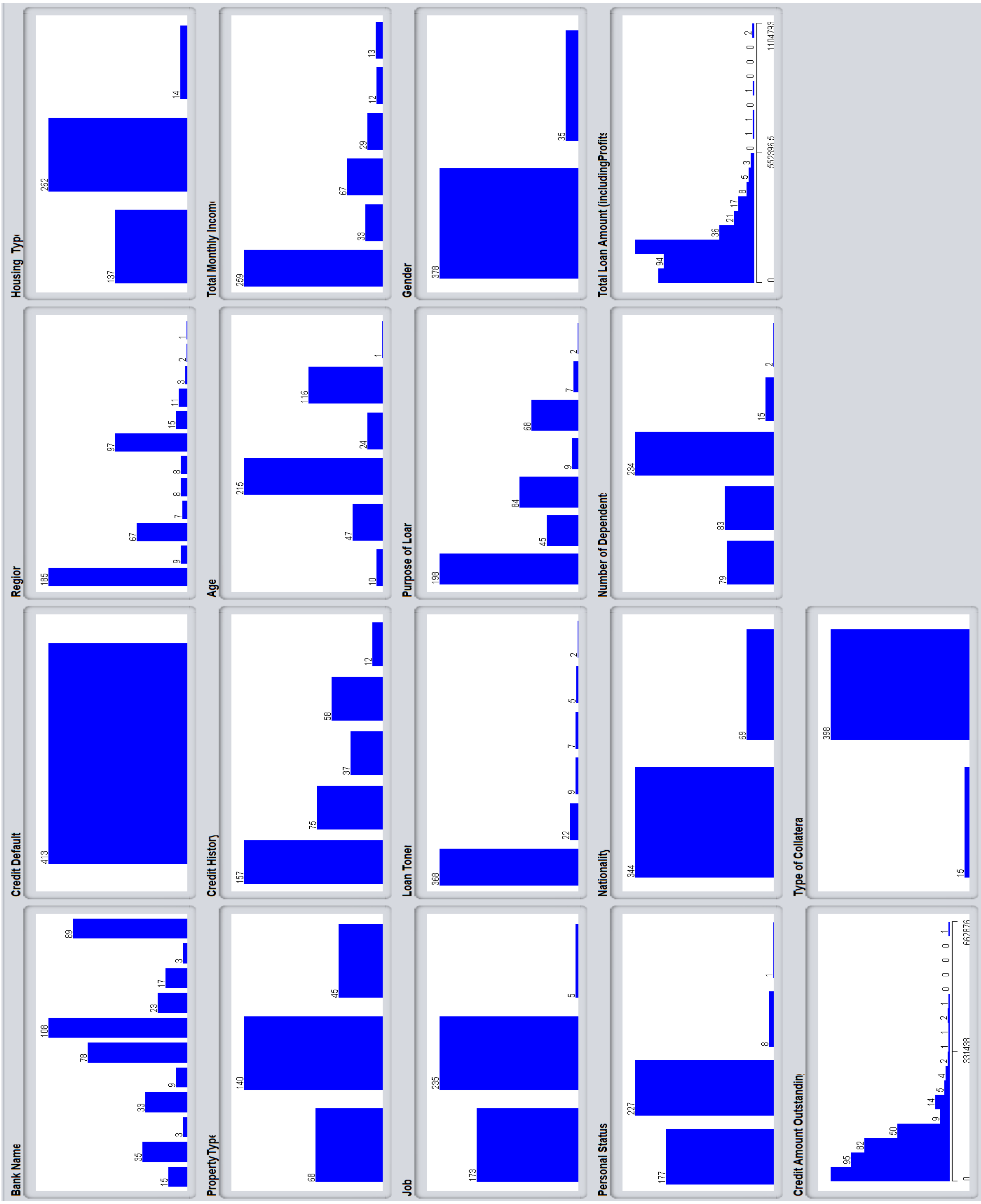

Figure 8 Bivariate analysis of the data during the pandemic.

With regard to the pandemic period, Figure 8 shows the relationship between each variable in the data set during the pandemic and the target variable “credit default.” Figure 8 shows that Riyadh ranks first with approximately 45% of defaulting loan applicants in the kingdom, followed by Makkah (23%) and the Eastern Province (16%). The data of 2020 also show that 63% of the defaulting loan applicants own their homes, with approximately 34% living in villas. Figure 8 also shows that during the pandemic, the majority of noncreditworthy clients are those who were delayed in paying their debts in the past. Therefore, looking closely at the age bar charts, we can conclude that clients aged between 25 and 35 are the least creditworthy (55%), followed by those aged between 36 and 45 (28%). Figure 8 also shows that 83% of the noncreditworthy applicants are Saudi citizens and that approximately 65% are applicants with a total monthly income between 5K and 10K. In most cases in which a default was observed, the purpose of the loan was not specified and was saved under the name of other personal loans. The results show that applicants in the private sector are more likely to default, with a percentage of 57%, and that the defaulting creditors are most often males with no dependants under their responsibility.

6. Empirical Results

In this section, we introduce the results obtained after clustering and supervised learning. Table 3 shows the different parameters obtained when the *k*-means algorithm was run on the data collected before and during the pandemic. The table also shows that in both cases, the majority of the defaulting customers observed belong to cluster 1, with approximately 44% of all defaulting applicants before the pandemic and 42% during the pandemic.

Table 3 Clustering setting using WEKA software.

Clustering Method	2018/2019	2020
Number of Clusters	3	
Number of Iterations	5	7
Initial Starting Points	(Random)	
Missing Values	Globally replaced with mean/mode	
Clustered Instances	C 0 (25%)	C 0 (31%)
	C 1 (44%)	C 1 (42%)
	C 2 (31%)	C 2 (27%)

Figure 9 shows the DT that we obtained using the J48 algorithm on the data collected before the pandemic. The performance of the testing phase using Weka software is summarised in Table 4. The performance of our proposed methods is evaluated using: precision, recall and F-measure metrics.

The precision rate of 1 for a class C means that every applicant affected to this class does indeed belong to it, but this rate does not inform about the number of applicants from this class that were not correctly classified. A recall rate of 1 means that every applicant from class C is labeled as belonging to class C but does not inform about the number of applicants that were incorrectly labeled as belonging to class C. In general, there is an inverse relationship between precision and recall, where it is possible to increase one at the cost of reducing the other. The F-measure combines recall and precision into a global measure.

The Matthews correlation coefficient (MCC) is also used in the experiments. The coefficient takes into account True Positive, False Positive and False Negative rates. It is seen generally as a balanced measure which can be used even if the classes are of very different sizes.

Table 4 Validation measures obtained with a decision tree using the J48 algorithm on the data collected before the pandemic.

FP[2] Rate	**Precision**	**Recall**	**F-Measure**	**MCC[3]**	**ROC[4] Area**	**Class**
0.124	0.633	0.644	0.639	0.518	0.746	C 0
0.205	0.767	0.848	0.805	0.639	0.838	C 1
0.104	0.721	0.603	0.657	0.527	0.743	C2

The cited performance measures are obtained when the cut-off is 0.5. However, changing this threshold might modify previous results and allows to catch a greater number of good or bad applicants. Graphical tools can also be used as an evaluation criterion instead of a scalar criterion, such as the area under the receiver operating characteristic (ROC). ROC curve shows how errors change when the threshold varies (Bouaguel et al, 2013). This curve situates positive instances against negative ones to allow finding the middle ground between specificity and sensitivity.

From Table 4 we notice the best classification results were obtained for C1, this may be due to the fact that this cluster has 42% of the observations (see Table 3), as it is known the more the number of observations increases, the more precise the model.

[2] FP rate : false positive rate
[3] The Matthews correlation coefficient (MCC)
[4] ROC (Receiver operating characteristic)

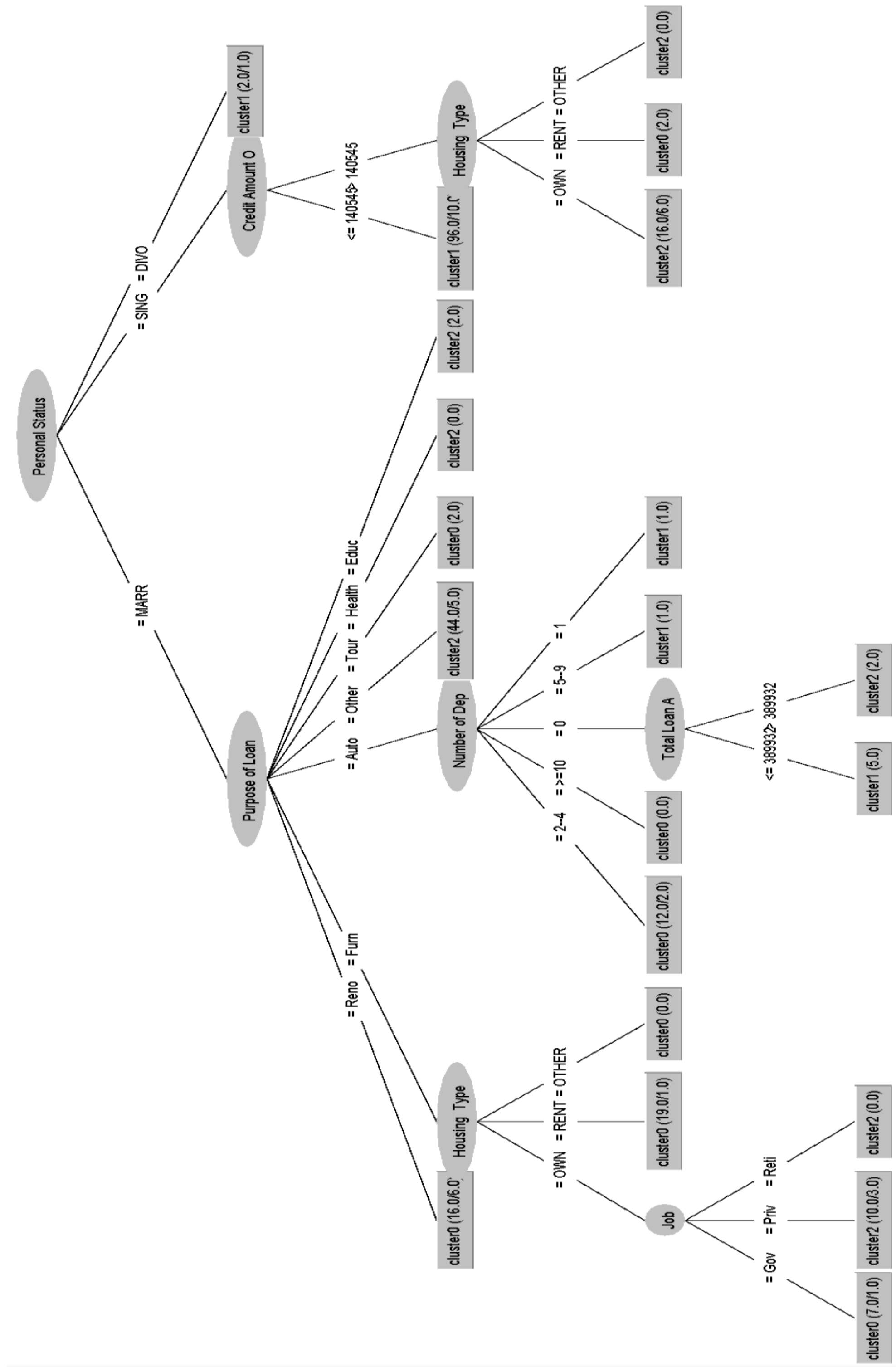

Figure 9: Visual representation of a decision tree outputted by WEKA (sample data before the COVID-19 pandemic).

Figure 9 shows that the root attributed to this model is personal status. Before the pandemic, applicants belonging to the first cluster (C0) were found to follow one of the following rules:

- Personal status = married; purpose of loan = renovation and home innovation
- Personal status = married; purpose of loan = furniture and consumer durables and goods; housing type = rented
- Personal status = married; purpose of loan = cars and automobiles financing; number of dependants = two to four
- Personal status = married; purpose of loan = furniture and consumer durables and goods; housing type = owned; job = government

Applicants belonging to the second cluster (C1) were found to follow one of the following rules:

- Personal status = single; outstanding credit amount ≤ 140,545
- Personal status = married; purpose of loan = cars and automobiles financing; number of dependants = two to four; total loan amount (including profits) ≤ 389,932

Applicants belonging to the third cluster (C2) were found to follow one of the following rules:

- Personal status = married; purpose of loan = other personal loans
- Personal status = married; purpose of loan = furniture and consumer durables and goods; housing type = owned; job = private
- Personal status = single; outstanding credit amount > 140,545; housing type = owned

From the previous rules, we can conclude that the most important characteristics of credit applicants before the pandemic are related to their personal status and the purpose of the loan. The results show that most of the applicants were married and that the purpose of the loan in most cases was to buy furniture and consumer durables and goods.

In this study, we used the J48 algorithm on the data collected for 2020. Developed by Ross Quinlan as an extension of the ID3 decision tree algorithm, the J48 algorithm is considered one of the most famous algorithms for generating DTs (J48 is implemented in WEKA using the weka.classifiers.trees.J48 classifier class). J48 is also regarded as a statistical classifier since it is used for classification. Table 5 summarises the performance of this algorithm.

Table 5 Validation measures obtained with a decision tree using the J48 algorithm on the data collected during the pandemic.

FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	Class
0.074	0.828	0.777	0.802	0.715	0.884	Cluster 0
0.104	0.863	0.913	0.888	0.804	0.943	Cluster 1
0.092	0.741	0.727	0.734	0.639	0.885	Cluster 2

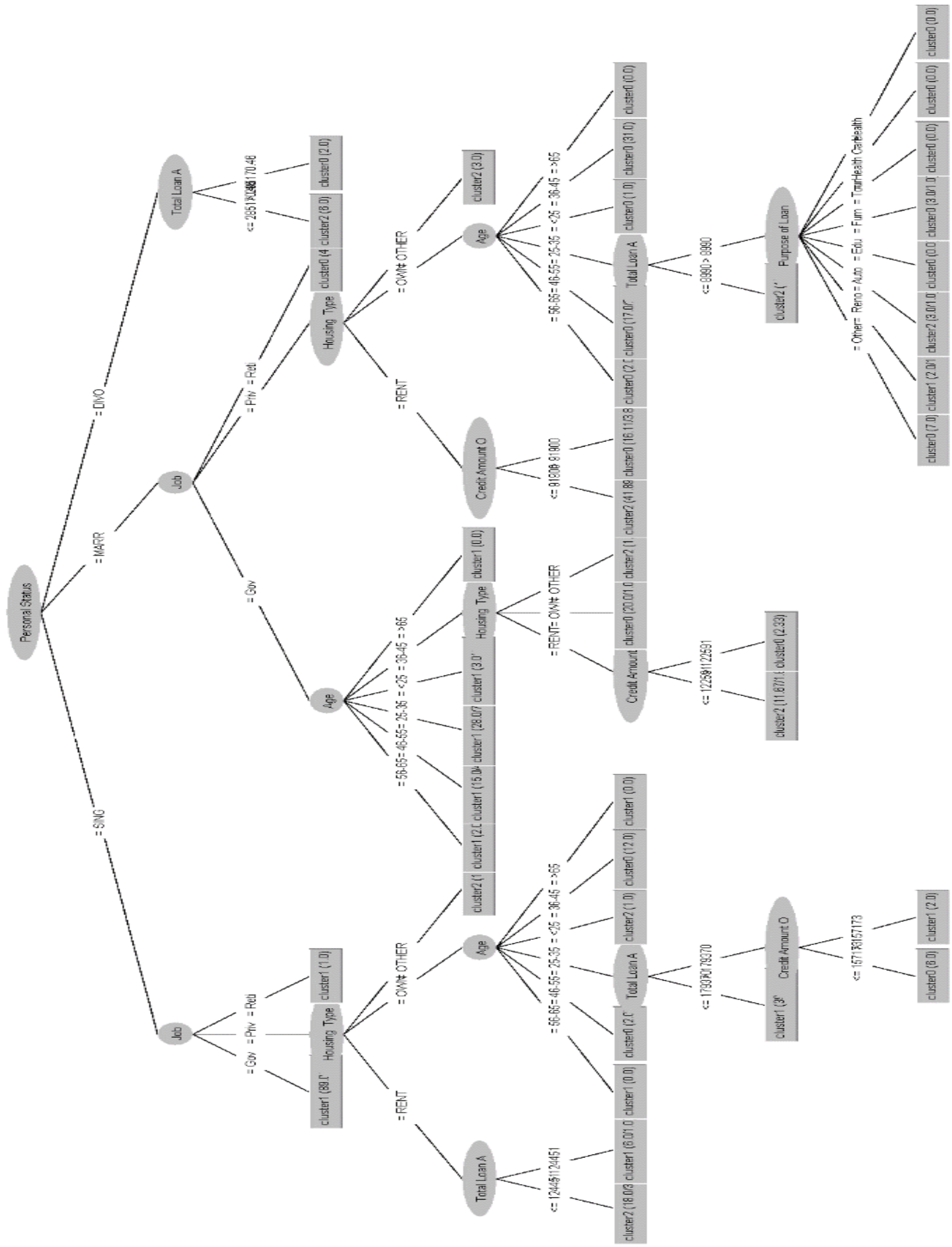

Figure 10: Visual representation of a decision tree outputted by WEKA (sample data during the COVID-19 pandemic).

Figure 10 shows that the root attributed to this model is personal status, similar to what has been reported regarding the data before the pandemic. During the pandemic, applicants belonging to the first cluster (C0) were found to follow one of the following rules:

- Personal status = married; job = private; housing type = owned; age = 36–45 years
- Personal status = married; job = private; housing type = owned; age = 46–55 years
- Personal status = married; job = government; age = 36–45 years; housing type = owned
- Personal status = married; job = private; housing type = rented; outstanding credit amount > 91,900

Applicants belonging to the second cluster (C1) were found to follow one of the following rules:

- Personal status = married; job = government; age = 25–35 years
- Personal status = married; job = government; age = 46–55 years
- Personal status = single; job = private; housing type = rented; total loan amount (including profits) > 124,451

Applicants belonging to the third cluster (C2) were found to follow one of the following rules:

- Personal status = married; job = private; housing type = rented; outstanding credit amount ≤ 91,900
- Personal status = married; job = government; age = 36–45 years; housing type = rented; outstanding credit amount ≤ 122,591

Overall, the rules obtained reveal a slight change from those obtained for the tree reporting the behaviour of non-creditworthy applicants before the pandemic. Clearly, the applicants' characteristics are heavily influenced by their job types, while before the pandemic defaulting was highly correlated to the purpose of the loan. In fact, before the pandemic, personal loans were obtained for different purposes, for example, a person who needs an important, life-saving surgery and, hence, needs to immediately deposit money at the hospital. In these situations, people usually tend to take a personal loan for health care. Another common reason for taking personal loans is to buy or renovate a house. Many customers seek renovation and home improvement loans to cover such extra funding requirements. However, sometimes they fall behind with their loan payments because of the accumulation of interests related to this type of loans. In fact, home innovation loans have been observed to slightly increase after the beginning of the pandemic, which may reflect more people starting remodelling projects while quarantining at home. With the spread of the pandemic, Saudi Arabia moved to a lockdown phase and took multiple measures on many economic levels, which had a particular effect on jobs in the private sector. Moreover, with the pandemic negatively affecting the private sector, individuals with low income and living in rented houses were found to be the category most affected by the pandemic. In fact, the pandemic had a negative impact on the employment and income of many people.

7. Conclusion

Generally, the abrupt advent of the COVID-19 pandemic, as well as the precautionary measures that were established to help prohibit its spread, took its toll on the global economy, with Saudi Arabia being no exception. After the first case of COVID-19 was recorded in the country, the Saudi government assessed the situation immediately and established urgent precautionary and robust measures to protect its citizens and expatriates. To mitigate the financial and economic impact resulting from the precautionary measures and provide support to the private sector during such hard times, the government prepared and introduced a set of urgent monetary and fiscal stimulus packages.

In this study, we use a variety of machine learning techniques to investigate the impact of COVID-19 on the Saudi consumer credit scoring. The empirical part of the study begins by outlining a univariate and a bivariate analysis of different data sets. The univariate analysis revealed that the number of credits with default has increased during the pandemic. In fact, approximately 45% of the defaulting credit was observed in 2020, the year of the pandemic. On the other hand, the bivariate analysis results indicated that 45% of the noncreditworthy applicants located in Riyadh before and during the pandemic and 60% of the defaulting applicants before the pandemic live in owned houses, in most cases in villas. The results also showed that during the pandemic, approximately 63% of the defaulting loan applicants were those who own their houses, with approximately 34% living in villas. The rest of the empirical part focusses on the implemented machine learning model (WEKA decision tree, J48 algorithm). The main results obtained with the J48 algorithm indicate that the most significant characteristics of credit applicants before the pandemic are related to their personal status and the purpose of the loan. We also found that the applicants' characteristics are heavily influenced by their job type during the pandemic year.

This research work has a few limitations. For example, the data available on defaulting applicants are limited. We used only the repayment information of 972 noncreditworthy applicants from a total of 47,662 observations during the study period. Hence, further research may add more observations from 2021, which may help overcome this limitation. It is also possible to extend the empirical analysis of this research using a mixture of clustering approaches over account profiles.

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