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Development of Demographic, Social and Economic Characteristics of the Beneficiaries of Microfinance Loans in Saudi Arabia Before and during the COVID-19 pandemic

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Abstract

Social banking and microfinance have become the key factors for developing and sponsoring the microenterprises sector as well as supporting low-income families and underprivileged citizens in any country. To better understand the situation of social banking and microfinance in Saudi Arabia, we propose in this paper a data-driven study of microfinance loans granted by the Saudi Social Development Bank (SDB) from 2015 to 2020. Our study mainly investigates the changes of demographic, social and economic characteristics of the beneficiaries, with a special emphasis on the COVID-19 repercussions, by using intelligent and recent machine learning and data analytics tools. Results reveal the important growth of social loans during the COVID-19 period as well the significant evolution of loans granted to women and to special needs individuals. Furthermore, a machine learning decision tree model has been built, for individual and business microcredits, to easily visualize the main beneficiary characteristics of each credit category before and during the COVID-19 pandemic. The built decision trees allowed to deeply understand the main characteristics of each credit category which will help managers to design more suitable and fitted microfinance products.

Keywords: *Social Banking, Microfinance Credits, Decision Trees, Multivariate analysis, COVID-19*

JEL Classifications: *G21, C38, C88, H8*

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1. Social Banking and Microfinance

Financial institutions have established different means of attracting and sustaining clients by developing and providing reliable banking programs such as social banking. The term 'social banking' refers mainly to the direct relationship between the lender and borrower without a goal of any positive social impact produced (Weber and Remer, 2011). Later on, in developing countries specifically, social banking is referred to as subsidized government or development banking mainly associated with microfinance or microcredit. It then used the socially oriented meaning in which it mainly and necessarily has a positive social impact. In this sense, social banks specialize in providing financial services to create social and sustainable benefits for individuals, corporations, and organizations. The primary principles that guide the operations of social banks are sustainability, inclusivity, transparency, and resilience (Weber, 2014). As a result, social banks operate in societies and communities where they directly support individuals, corporations and organizations and help them to benefit from their social and economic activities.

Unlike commercial banks, which emphasize on business transactions and profit maximization, social banks focus on the relationship between the client and the financial institutions by finding out means to develop and support their clients' businesses (Ariani, 2016). Therefore, social banks take the leadership role between financial institutions and individuals, corporations or organizations. Social banks focus on ethical and social nature of banking. Social banking stimulates economic growth throughout the country and thus raises the level of living of the target individuals. The spillover effect of enhancing financial independence of individuals and families is extended to communities and societies where it does not neglect financial sustainability, and the impact of the investment that is felt by the community (Ariani, 2016).

Our research study emphasizes the social and microfinance sector in Saudi Arabia by studying social and microloans granted by one of the most important engines of this sector, the Social Development Bank (SDB), during the last five years. The SDB in Saudi Arabia was established in 1971 and is considered a key institution in assisting and developing the social and economic funding to citizens. It mainly intends to enhance and improve the financial independence of individuals and families via providing financial and non-financial services to assist in reaching and sustaining an active and productive community, society and economy at large.

An overview of the major social and financing programs will be enumerated and discussed. In addition, an analytical analysis of the granted loans will be deeply studied. Our objective is to study the main changes in the characteristics (demographic, social and economic) of the beneficiaries of social loans, subsidies, and microfinance during the last five years in Saudi Arabia. Furthermore, the study will focus upon the repercussions of the COVID-19 pandemic on the characteristics of social and microfinance beneficiaries in Saudi Arabia. It is important to mention that the role of social banks during crises is very essential to support low-income families and individuals and micro and small enterprises.

The analytical study will be performed using intelligent and recent machine learning and data analysis tools including univariate, multivariate and classification techniques. Appropriate and auto-fitted decision tree classification models will be evaluated in order to extract pattern and hidden knowledge from descriptive data of social loans and microfinance beneficiaries. The objective is to build main characteristics (profiles) of the beneficiaries of social and microfinance loans during the last five years. Theses beneficiaries' profiles will help firstly to inspect the suitability of the beneficiaries of social and microfinance loans (granted from 2015 to 2020) with the general government policies and secondly help financial institutions and authorities to design more efficient fitted programs and measures for such types of loans.

The rest of this paper is organized as follows. Section 2 gives an overview of microfinance and social funding products provided by the SDB while Section 3 describes the data collection and preprocessing tasks that we performed to build the data of social and microfinance loans granted by the SDB from 2015 to 2020. Then, Section 4 presents the univariate and bivariate analyses of the evolution of main characteristics of microloans and its beneficiaries while Section 5 describes the main characteristics of social loans before and during the COVID-19 pandemic for each credit category built by using the machine learning decision tree method. Finally, Section 6 presents the conclusion and future works to improve this study.

2. Overview of Microfinance and Social Credit Programs in Saudi Arabia

One of the key institutions in assisting and developing social and economic micro funding to Saudi citizens is the SDB. It has the objective of enhancing and improving the financial independence of individuals and families via providing financial and non-financial services to assist in reaching and sustaining an active and productive community, society and economy at large. A variety of programs has been implemented to assist in reaching these goals through facilitating the access to social financing and introducing several products and business solutions that help in the improvement of the low-income citizens and the development of society. During the last 50 years, the SDB served more than 2.7 million citizens with roughly 120 billion Saudi Riyal (SAR) in around 180 thousand projects (SDB, 2021). The bank's products and programs can be classified into three major categories: individuals, businesses, and charitable organizations. Loans granted to individuals mainly focus on improving their social and economic situation through six essential programs: Family Loan, Marriage Loan, Restoration loan, NFADH, Kanaf Product, and Zood Saving Product. Each program targets a specific group of society. It aims to identify solutions, to solve business problems and satisfy the needs of each group in society. In Table1 a brief description is illustrated for each program and products provided to individuals and the number of beneficiaries in total as reported by the SDB (SDB, 2021).

Furthermore, many programs have been initiated to support businesses. As seen in Table 2, a list of eleven programs that are intended to support numerous kinds of micro and small businesses and investment projects, which include and not limited to, invention projects, technology, vending cars, franchise programs. The SDB also supports the charitable organizations or so called "third sector". The bank facilitates financing to the third sector to improve and activate the role of associations in switching from pastoral work to broader development work through the provision of microfinance services to support beneficiaries towards microeconomic activities in which they support productive families and enterprises in general. Table 3 shows the programs provided by the SDB to the charitable organizations.

Table 1

Social-loan programs provided to individuals as of March, 2021.

Program	Program Description	Number of Beneficiaries
Family Loan	Provided to low-income families assisting them in coping with the cost of living.	Approximately 1,118,166
Marriage Loan	Provided to male citizens whose monthly income is equal or less than SAR 10 thousand to assist and encourage them in getting married.	Around 2,201,089
Restoration Loan	Provided to citizens for the purpose of rebuilding and renovating their houses.	Approximately 195,000
NFATH	Provided to citizens who are looking for jobs or low-income working citizens, receiving SAR14 thousands or less, who have professional skill or craft who can be benefiting from starting up their own businesses to help them make or increase their own income.	New initiative
Kanaf Product	Provided to widowed and divorced females with up to SAR 30 ‘ othousands.	Around 14,058 females.
Zood Saving Product	Provided to citizens from both genders to encourage the growth of saving.	About 9,327

It is worth mentioning that the SDB has provided initiatives to assist in mitigating the negative impacts of COVID-19 on low-income productive families and small establishments. According to an announcement by the SDB in February 2021 (SDB, 2021), over 54,000 beneficiaries have benefited from these initiatives during the pandemic. In addition, the SDB also offered grace periods for beneficiaries impacted by the economic fallout caused by the pandemic. All these important measures come as the Saudi government explores ways to support the local economy, which has been affected by the coronavirus outbreak. The SDB has initiated some programs, as a form of support to individuals and businesses, in order to help citizens, micro enterprises and small businesses to overcome their financial difficulties due to the COVID-19 pandemic.

Table 2

Types of social-loan programs provided to businesses as of March 2021.

Program	Description
Business Incubators and Accelerators product	A product to finance businesses with small size projects in which the investment cost is between 300,000 SAR and 8 million SAR.
Emerging Technologies Product	A product to finance projects for gifted Saudis related to new digital enterprises to improve business environment and open doors and opportunities for Small and Medium Enterprises SMEs in the high priority sectors. The projects should meet at least one of the excellence criteria set by the SDB and the project investment costs should exceed 300,000 SAR.
Ayed	A product provided to start-ups and micro enterprises in industrial and emerging businesses in collaboration with SABIC NUSANED.
OSOS Program	A loan product provided by the SDB in collaboration with the Saudi Authority for Industrial Cities and Technology Zones (MODON) to encourage and empower Saudi young entrepreneurs to start up industrial businesses in industrial cities.
Hal "Solution" Saudization Project	A product to finance resettlement projects which provides financial and non-financial services for 12 business activities that started in early 2018. The funding ranges between 50,000 SAR and 1 million SAR.
Excellence Projects Program	A product to finance small size projects in which its investment cost ranges from 30,000 SAR to 8 million SAR.
Franchise Program	Funding services provided to qualified citizens to invest in small size business activities with high success rates and low risk ratios in coordination with some national and international brands to grant a commercial franchise.
Mobile Vending Trucks	A funding that supports up to 250,000 SAR to citizens starting up micro-projects in the field of mobile vending carts.
Invention Projects Program	A program that aims to support inventors to implement their inventions and transform them into successful commercial projects.
Graduates Program	A program that accommodates qualified graduates, who are prepared to teach, as well as holders of diploma in health, by helping them create small and emerging projects that correspond to their major and specialization.
Emerging Projects Program	A program to finance citizens to invest in small and start-up projects in which the investment cost would not exceed 300,000 SAR.

For instance, based on the information published by SDB in March, 2021 many of the new initiatives such as "Daeem" and other programs have supported individuals with total financial lending that reached 12 billion SAR with 4 billion SAR allocated to low-income individuals and families since the emerging of COVID-19 pandemic. Also, it provided around six months grace period for beneficiaries and increased the financial support to micro and small businesses during the COVID-19 pandemic by about 2 billion SAR to help around 6 thousand entrepreneurs in initiating and operating their businesses. Moreover, the support was also provided to new small and medium health centers by creating a new wallet with a total amount of 2 billion SAR that supported approximately 1000 small and medium health centers which has helped them improve their operational capacity and quality of services.

Table 3

Types of social-loan programs provided to charities as of March 2021.

Program	Description
Tamkeen	A financing product provided to Charities - social development committees - development finance institutions - non-profit institutions that intends to activate the role of associations in switching from pastoral work to broader development work through the provision of microfinance services to support beneficiaries towards micro-economic activities in which they support productive families and micro-enterprises.
Sahim	A financing product provided to cooperative organizations that aims to improve the economic and social conditions of the members in terms of production, consumption and marketing. It is funded by the registered cooperative organizations in the Ministry of labor and social development.
Daeem	A development finance product that intends to motivate non-government organizations and social development committees to sustain and diversify their source of income.

To better understand the situation of social credits and microcredits in the Kingdom of Saudi Arabia, we propose a data analytics study of microfinance loans granted by the SDB during the last five years. The study emphasizes main demographic, social and economic characteristics of the beneficiaries of social loans, subsidies, and microfinance during the last 5 years, including the repercussions of the COVID-19 pandemic, by using intelligent and recent machine learning and data analysis tools. Appropriate and auto-fitted classification techniques will be designed in order to extract pattern and hidden knowledge from descriptive data of social loans beneficiaries. The objective is to identify the main characteristics of social loans beneficiaries to help the government and banks better identify the classes of beneficiaries and then help managers to design more efficient fitted programs and measures for these classes.

3. Empirical Analytic Methodology for the Analysis of the Beneficiaries Characteristics of Micro-loans

3.1. Data analytics methodology

Data analytics is a collection of fundamental methods, principles and tools that support and guide the extraction of information and understanding from data. It entails the use and development of algorithms, methods, procedures, and techniques for improving decision-making by comprehending past, present, and future occurrences through data analysis. To maximize the benefits of data science and analytics, data scientists and analysts must be able to see business problems through the lens of data. The financial data analysis is one of the world's largest applications of data analytics.

In our case, two types of data analytics techniques will be performed: descriptive analysis (univariate and bivariate analysis) and exploratory analysis. In the first analysis type, we will summarize collected data on each variable separately from 2015 until 2020. We considered the year 2019-2020 as the period of COVID-19 pandemic. A second descriptive bivariate analysis will be performed by studying changes in each variable respecting credit categories. For each credit category, we will report a mosaic of a bivariate analysis of the variable for the years 2019 and 2020. Our objective is to first analyze social loans based on credit classes and then detect any changes in the characteristics of social loans and their beneficiaries before and during the COVID-19 pandemic

After that, an exploratory data analytics process will be performed by using machine learning decision trees. This process aims to build main beneficiaries profiles before and during the pandemic for individual and business micro-credits separately. We modeled the profiling process as a classification problem by considering credit categories as the desired classes that can be solved using a machine learning decision tree. The most important characteristics of each credit class can be interpreted from the tree by describing most important paths towards the leaves of the tree representing each credit class. In order to build the best decision tree model for individual and business credits, we will evaluate three types of algorithms for the years 2019 and 2020 separately (J48 (Quinlan, 1996) , J48 Consolidated (Igor et al, 2015) and REPTree (Weka, 2021)). The objective is to determine the best tree in terms of classification error which gives visual profiles of the beneficiaries of social loans.

3.2.Data Collection and Preprocessing

Our study is based on the social and microfinance loans data granted by the Saudi SDB from 2015 to 2020. We collected all published data from 2015 to 2020 of the SDB at the Saudi open data platform[1].We considered two main categories of social and microcredit: Individual and Business loans. Individual credits are those provided to individuals to support their social and economic situation. This category of credit is sub-classified into six main classes (categories) which are respectively: 1- Association, 2-Cash, 3-Family, 4-Marriage, 5-Private, 6-Restoration. The second category of loans is the business category which is provided to support a new or an existing business project and is sub-classified into nine categories as follows: 1-Emerging Projects, 2- Excellence, 3-Franchise Program, 4-Graduate Program, 5- PrivateCAB, 6- Quaem, 7-Solution, 8- Vending Cars, 9- Others. We considered different numeric, binary and categoric characteristics for the description of loans and their beneficiaries. These characteristics can be classified into demographic, social and economic characteristics. Table 4 describes all used variables and the considered levels for each variable.

[1] https://data.gov.sa/Data/en/organization/social_development_bank

Table 4

Characteristics of variables considered for the description of social loans and their beneficiaries.

Categorization	Variable Name	Variable Type	Variable Levels
Demographic	Beneficiary Sex	Binary	Male, Female
	Beneficiary Age	Categoric	< 30, >= 30 , >= 40 , >= 60
Social	Social Situation	Categoric	Abandoned Woman, Divorced, Married, Single, Widower
	Special Needs	Binary	Yes, No
	Family Members	Categoric	< 02,>= 02,>= 05,>= 10
Economic	Saving Credit	Categoric	Yes, No
	Incomes Amount	Categoric	< 5000, >= 10000, >= 5000, >= 7500
	Credit Amount	Numeric	
	Credit Type	Categoric	Individual, Business
Credit class	Credit Class	Categoric	**For individual credit:** 1- Association , 2-Cash, 3-Family, 4-Marriage, 5-Private, 6-Restoration **For business credit:** 1-Emerging Projects, 2- Excellence, 3-Franchise Program, 4- Graduate Program, 5-PrivateCAB, 6- Quaem, 7-Solution, 8-Vending Cars, 9- Others

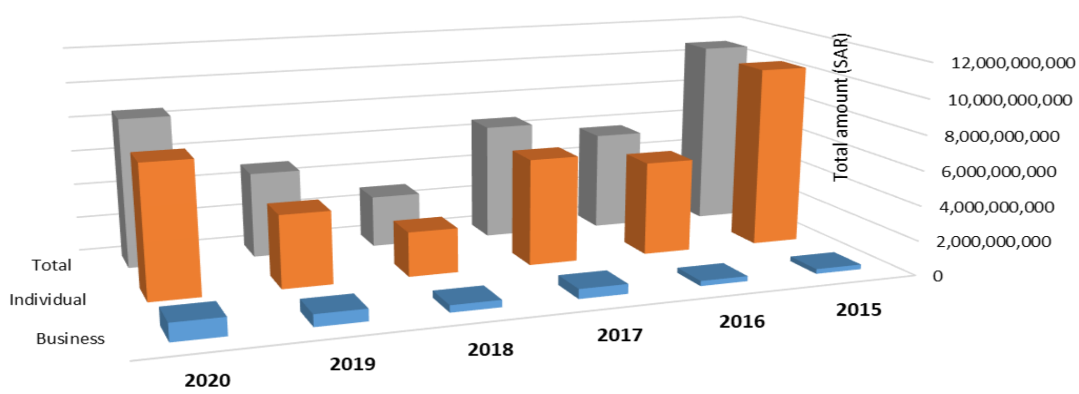
4. Univariate and Bivariate Analysis of the Evolution of Main Characteristics of the Beneficiaries of Microloans

4.1. Univariate Analysis of Microloans and its Beneficiaries

We studied the evolution and the changes observed on each descriptive variable separately from 2015 to 2020. Figure 1 and Figure 2 report the evolution of total amounts and the total number of social loans accorded by the SDB from 2015 to 2020. These two figures show the important evolution of both individual and business credits for the year 2020 in terms of number and value.

Figure 1

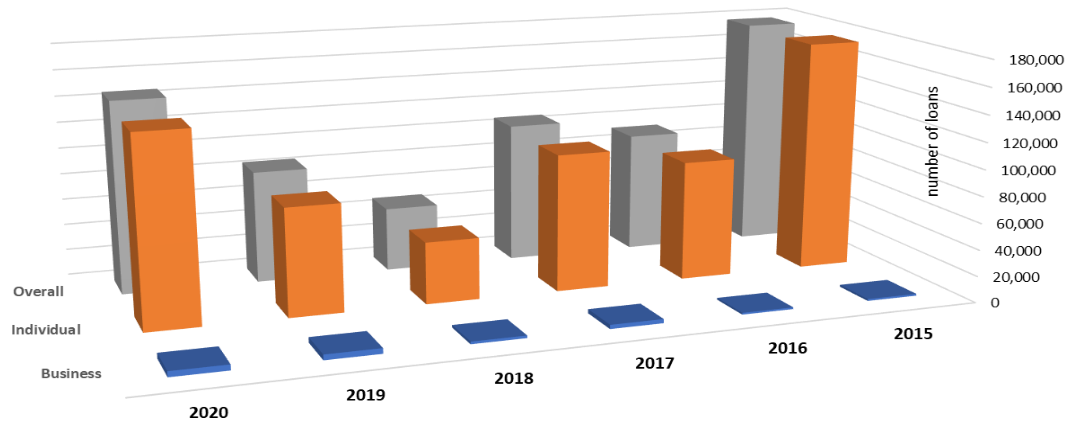
Total amount (SAR) of social and microloans between 2015 and 2020 accorded by the SDB.



	2020	2019	2018	2017	2016	2015
Business	1,018,320,857	686,064,201	405,625,386	558,395,541	291,188,667	273,432,565
Individual	7,579,100,194	4,173,838,000	2,567,493,000	6,152,614,000	5,432,421,000	10,479,061,000
Total	8,597,421,051	4,940,335,419	2,975,590,538	6,713,329,541	5,726,854,587	10,783,708,975

Figure 2

Total number of social and microloans between 2015 and 2020 accorded by the SDB.



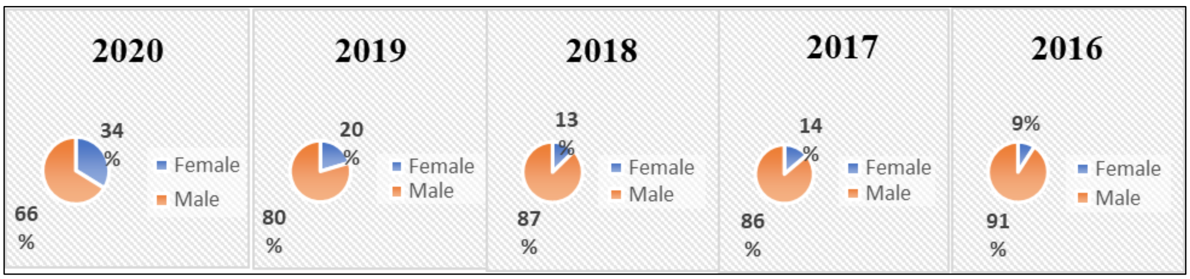
	2020	2019	2018	2017	2016	2015
Business	4,182	4,057	1,905	3,082	1,331	1,413
Individual	142,223	81,369	46,808	104,210	91,000	175,812
Overall	146,405	85,426	48,713	107,292	92,331	177,225

Compared to the four previous years (from 2016 to 2019), a significant growth has been noticed for the year 2020. The overall growth rate for the period 2019-2020 in terms of number of credits is evaluated by 71.4 percent which largely exceeds the Compound Annual Growth Rate (CAGR) evaluated by 12.2 percent for the period 2016-2020. This can be explained by the exceptional programs and efforts that the Saudi government has been making to support low-income families and small businesses during the COVID-19 pandemic, which started in March 2020.

Our univariate analysis of the main characteristics of loans and its beneficiaries during the last five years has also revealed two other important findings: the remarkable evolution of loans granted to women and the significant evolution of loans granted to people with special needs. Figure 3 reports the percentage of males and females of social and microcredit during the last five years. This figure shows a remarkable development of the total amounts of social loans that Saudi women are benefiting from year to year. For example, the females' percentage exceeds 34 percent of total amount of loans for the year 2020 while it was only 9 percent in 2016.

Figure 3

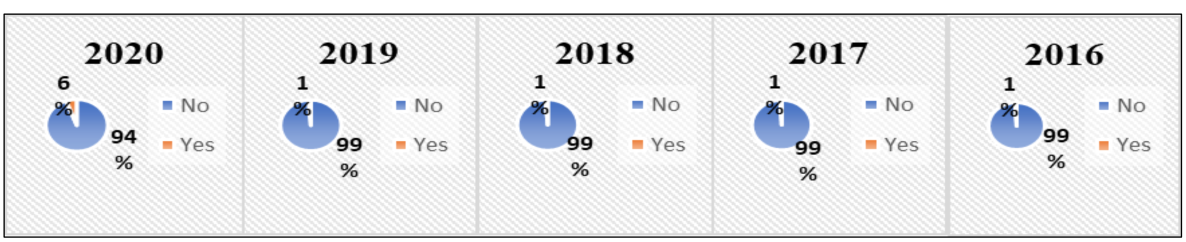
Distribution of loans between males and females in terms of value between 2016 and 2020.



In addition, we report in Figure 4 the percentage of loans granted to people with special needs which also shows an important growth for the year 2020. While it was only one percent for the last four years, the percentage of people with special needs exceeds six percent of total amounts of loans in 2020. These findings are well aligned with the exceptional government efforts in recent years to support and encourage these two social segments.

Figure 4

Percentage of special needs' individuals in terms of value from 2016 to 2020.



4.2.Bivariate Analysis of Microloans and their Beneficiaries based on Credit Classes.

We conducted experiments on individual credits and business credits separately. For each category of credit, we report a mosaic of a bivariate analysis of each variable by the credit categories for the years 2019 and 2020. Our objective is to first analyze social loans based on credit classes and then detect any changes in the characteristics of social loans and their beneficiaries before and during the COVID-19 pandemic.

4.2.1. Bivariate Analysis of Individual Credits based on Credit Classes.

Figures 5 and 6 report the distribution of individual credits for the years 2019 and 2020 respectively. Results are reported for each variable in the dataset by credit class which are respectively: 1- Association, 2-Cash, 3-Family, 4-Marriage, 5-Private, 6-Restoration. We give a description of each characteristic for the years 2019 and 2020 simultaneously.

- **Bivariate analysis by beneficiary sex:** we notice from Figures 5(a) and 6(a) that the total amounts of loans provided to females has increased for the year 2020 compared to the year 2019. We notice that for males there are three most dominated classes of loans, which are respectively cash, family and marriage. However, we show only one category, cash loans, that was mostly granted to females.
- **Bivariate analysis by beneficiaries age:** we notice from Figures 5(b) and 6(b) a decrease in the total amounts of social loans granted to the age group over 60 years for the year 2020 compared to the year 2019. We notice that age groups '<30' and '30-40' represent more than 65 percent of beneficiaries for both years 2019 and 2020. This shows that most of the beneficiaries of social loans are young people, indicating

the difficulties that the young age group finds in building their financial independence compared to the other age groups. Most of the granted loans for the age group ‘<30’ were of type ‘marriage’. A decrease is shown for the year 2020 compared to 2019. However, for the age group ‘40-60’, most of social loans were of type ‘family’ and has shown an increase during the COVID-19 pandemic compared to the period just before the COVID-19 pandemic.

- **Bivariate analysis by social situation:** we notice from Figures 5(c) and 6(c) an increase of total amounts of social loans provided to ‘single’ people for the year 2020 compared to 2019. However, ‘married’ couples remain the majority group for those benefiting from social loans for both years 2019 and 2020. Furthermore, we notice that for married couples, most of the social loans from which they benefited in 2019 were of type ‘family’ and ‘cash’ while in 2020 we show an increase of ‘marriage’ credits.
- **Bivariate analysis by special needs individuals:** we notice from Figures 5(d) and 6(d) an important growth of total amounts of social loans provided to special needs individuals for the year 2020 compared to 2019. We remark that the distribution of credit classes for people with special needs is similar to normal persons before and during the COVID-19 pandemic. This means that there is not any special credit product for special needs individuals, but they may have been given more priority than other normal persons to benefit from social loans for the year 2020.
- **Bivariate analysis by saving credit:** We notice from Figures 5(e) and 6(e) a slight decrease of total amounts of social loans provided to customers having a saving

program for the year 2020 compared to 2019. This may be explained by the unexpected financial pandemic after the decision of the government to close many commercial sectors to fight the COVID-19 repercussions. We also show from these figures that customers with a saving program have almost benefited from social loans of the type ‘family’ for both years 2019 and 2020. For beneficiaries without a saving program, we notice a change in the most commercialized credits before and during the pandemic. Before the pandemic, most loans were of the type ‘marriage’ while most loans were of the type ‘cash’ during the pandemic.

- **Bivariate analysis by family members:** We notice from Figures 5(f) and 6(f) a remarkable change in the group of family members who mostly benefited from social loans before and during the COVID-19 pandemic. In 2019, most beneficiaries belonged to the category ‘5 to 10’ while in 2020 most beneficiaries belonged to the category ‘<2’. In 2019, most beneficiaries of the category ‘5 to 10’ benefited from social loans of the type ‘family’ while in 2020 most beneficiaries of the category ‘<2’ benefited from social loans of the type ‘cash’.
- **Bivariate analysis by income amount:** We show from Figures 5.(g) and 6.(g) that the category with monthly incomes less than 5000 SAR is the category which mostly benefited from social credits before and during the COVID-19 pandemic. The only shown changes for this category are the types of social loans that have benefits. Before the pandemic, social loans of the type 'family' were widely granted for the category having an income amount less than 5000 SAR while during the pandemic we notice two types of credits that were mostly dominant namely 'family' and 'cash'.

Figure 5

Bivariate analysis of individual loans characteristics by credit class for the year 2019.

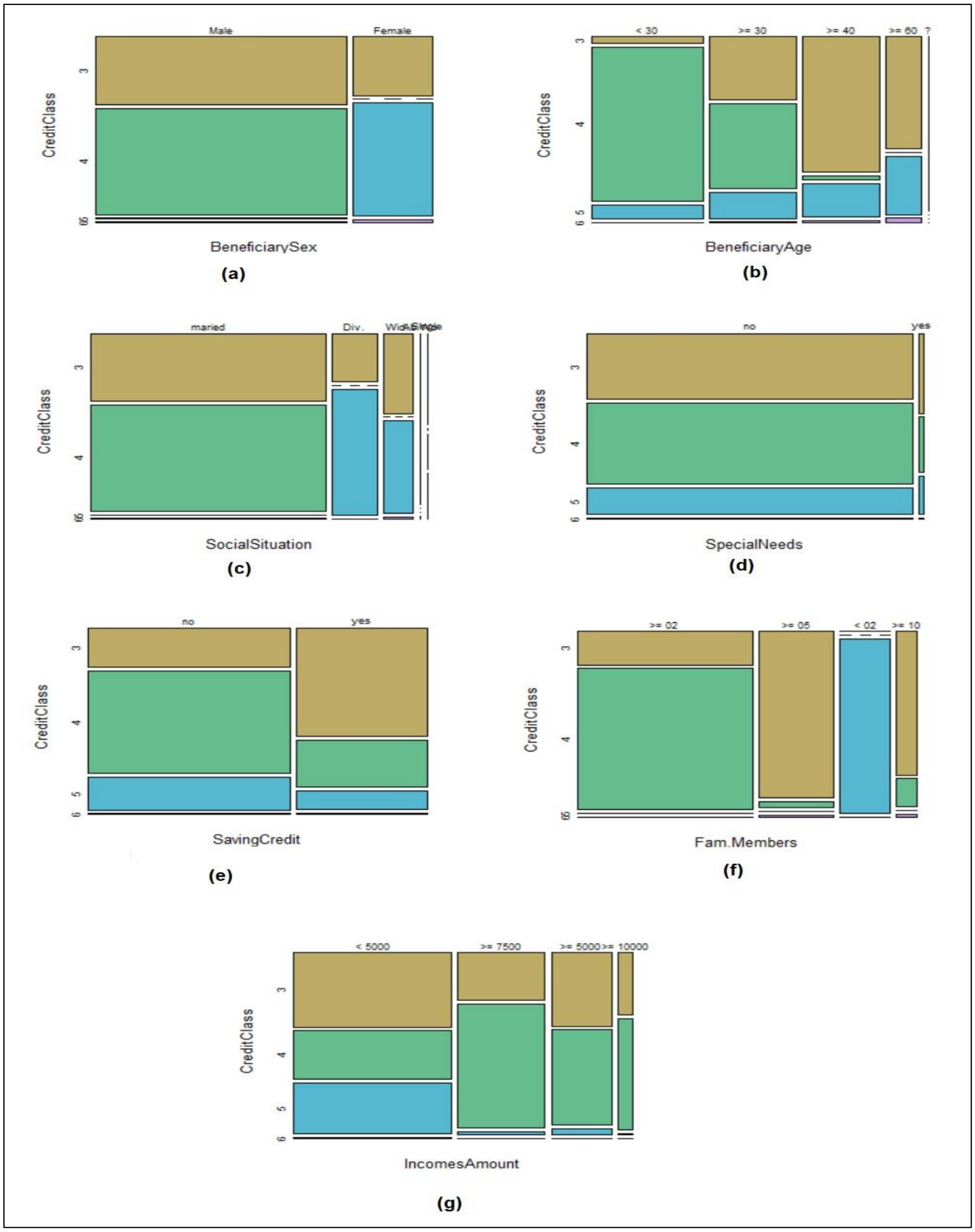
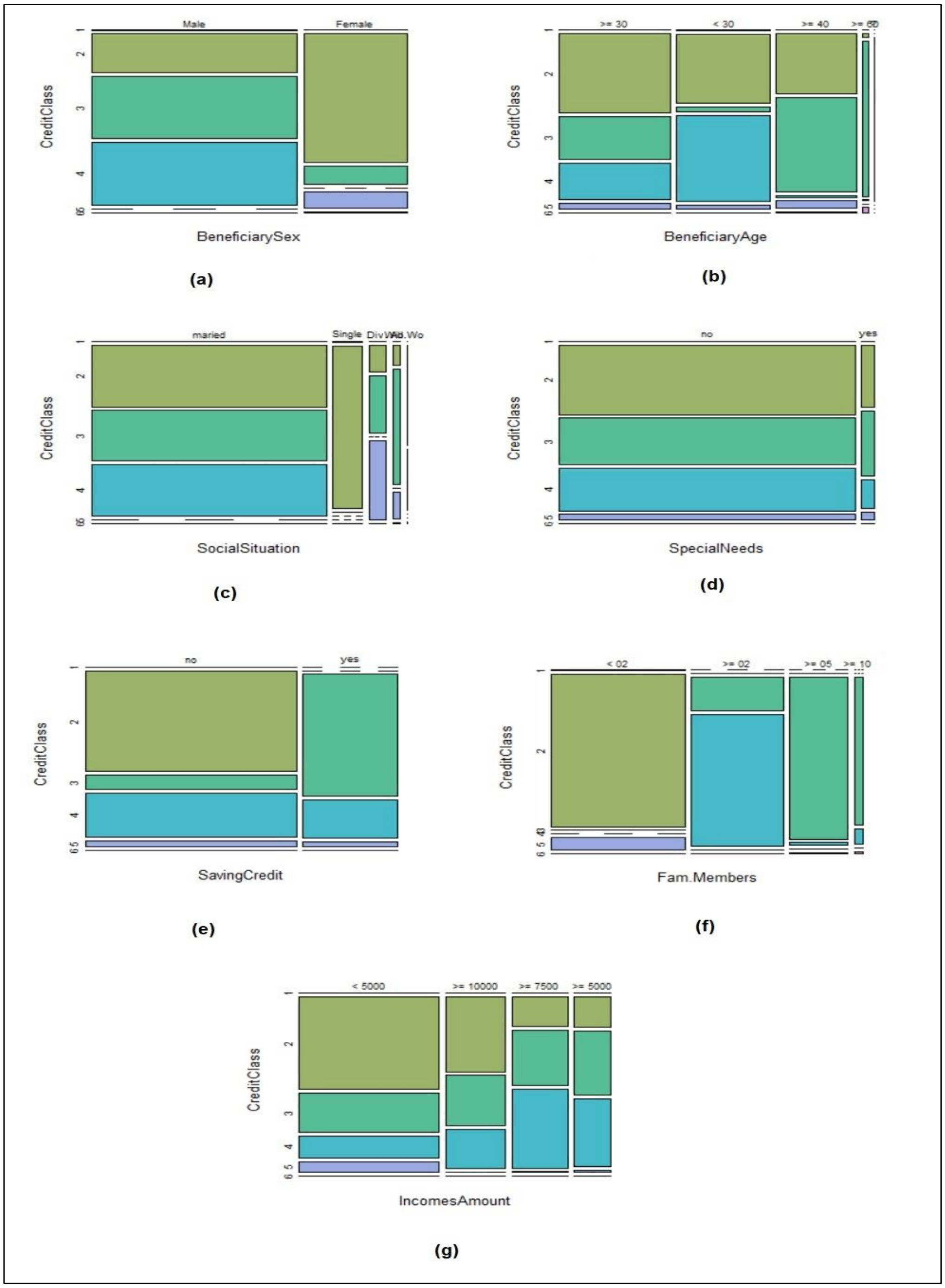


Figure 6.

Bivariate analysis of individual loans characteristics by credit class for the year 2020.



4.2.2. Bivariate Analysis of Business Credits based on Credit Classes

Figures 7 and 8 report the distribution of business credits for the years 2019 and 2020, respectively. Results are reported for each variable in the dataset by credit classes which are respectively: 1-Emerging Projects, 2-Excellence, 3-Franchise Program, 4-Graduate Program, 5-PrivateCAB, 6-Quaem, 7-Solution, 8-Vending Cars, 9-Others. We provide an analysis of each characteristic for the years 2019 and 2020 simultaneously. We note that the variable 'Saving credit' is omitted since all business loans are provided without any saving program.

- **Bivariate analysis by beneficiary sex:** We notice from Figures 7(a) and 8(a) that total amounts of loans provided to males and females remained the same for the years 2020 and 2019. We notice that, for males, the three most dominated classes of loans are 'emerging projects', 'private CAB' and 'solution' and this before and during the COVID-19 pandemic. However, for females, we show that women were benefiting from the class of loans 'Quaem' more than males during the COVID-19 pandemic.
- **Bivariate analysis by beneficiaries age:** We notice from Figures 7(b) and 8(b) that there is no change in the distribution of business loans before and during the COVID-19 pandemic based on the beneficiaries age. There is a balance between three age groups benefiting from social business loans, which are respectively '<30', '30 to 40' and '40 to 60'.
- **Bivariate analysis by social situation:** We notice from Figures 7(c) and 8(c) that there is no change in the distribution of business loans before and during the COVID-19 pandemic based on the social situation. Most of social business loans were provided equally to two categories, which are respectively 'married' and 'single' for

both years 2019 and 2020. However, during the COVID-19 pandemic, we notice an increase of total amounts of microfinance funding of the type ‘private CAB’ that were provided to the category ‘single’ compared to the period just before the COVID-19 pandemic.

- **Bivariate analysis by special needs’ individuals:** We notice from Figures 7(d) and 8(d) a growth of total amounts of microfinance loans provided to special needs’ individuals for 2020 compared to 2019. In 2019, the most dominated type of credits granted to people with special needs was ‘private CAB’. However, during the COVID-19 pandemic, we notice a remarkable change of credit types that were granted to this category of customers. There is a balance between 4 types of microfinance loans, which are respectively ‘emerging projects’, ‘graduate program’, ‘private CAB’ and ‘solution’.
- **Bivariate analysis by family members:** We notice from Figures 7(e) and 8(e) that there is no change in the distribution of business loans before and during the COVID-19 pandemic based on the family members variable. However, we notice an important thing compared to individual credits: more than 80 percent of beneficiaries of microfinance loans belong to the category ‘<2’. This is different for individual social credits where it was a balance between three categories of family members which are respectively ‘<2’, ‘2 to 5’ and ‘5 to 10’.
- **Bivariate analysis by income amount:** We show from Figures 7(e) and 8(e) that there is also no change in the distribution of business loans before and during the COVID-19 pandemic based on the income amount variable. For both years 2019 and

2020, the category with a monthly income less than 5,000 SAR benefits of more than 85 percent of the total amount of business loans. The three most dominated classes of business credits were ‘emerging projects’, ‘private CAB’ and ‘solution’.

Figure 7

Bivariate analysis of business loans characteristics by credit class for the year 2019

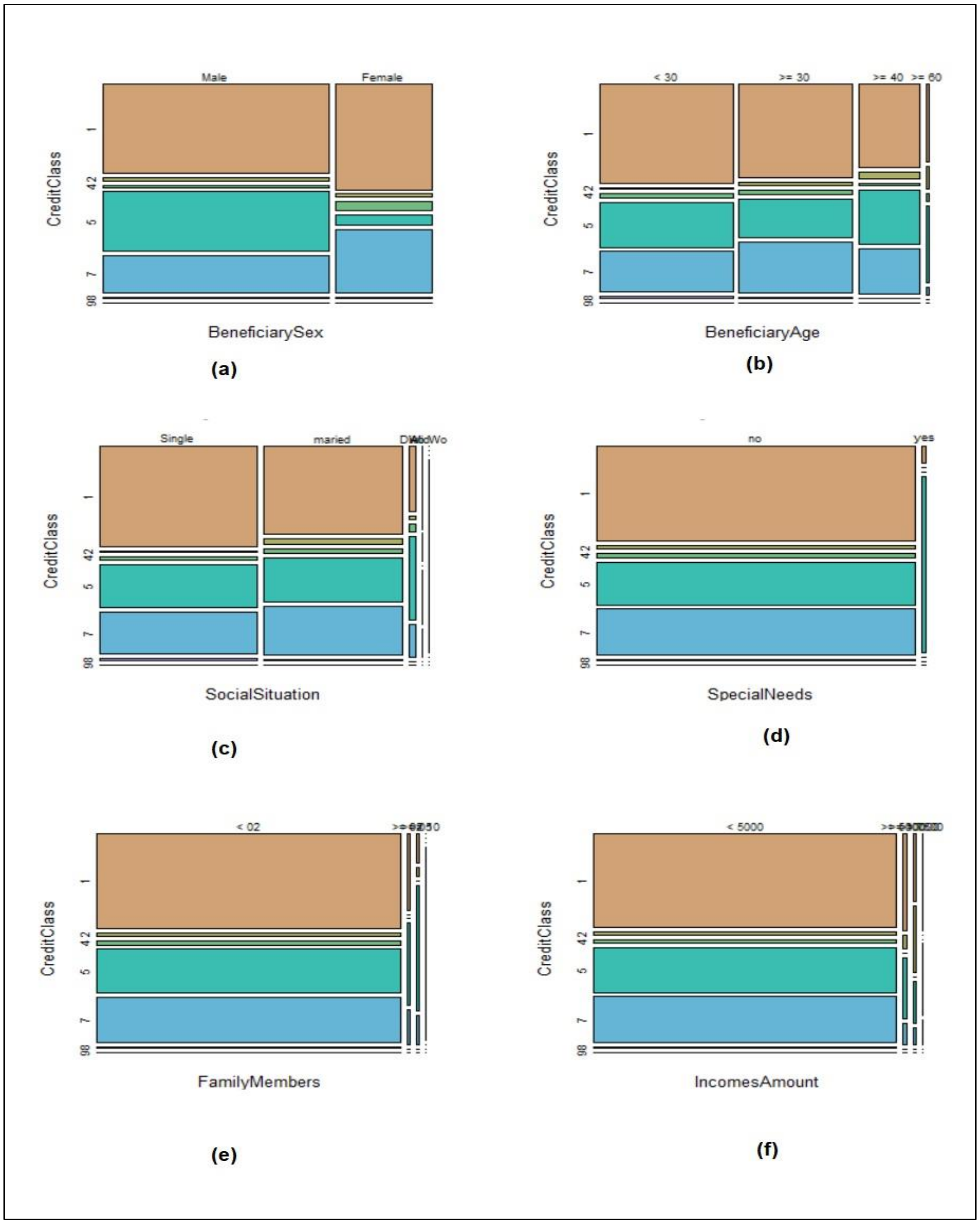
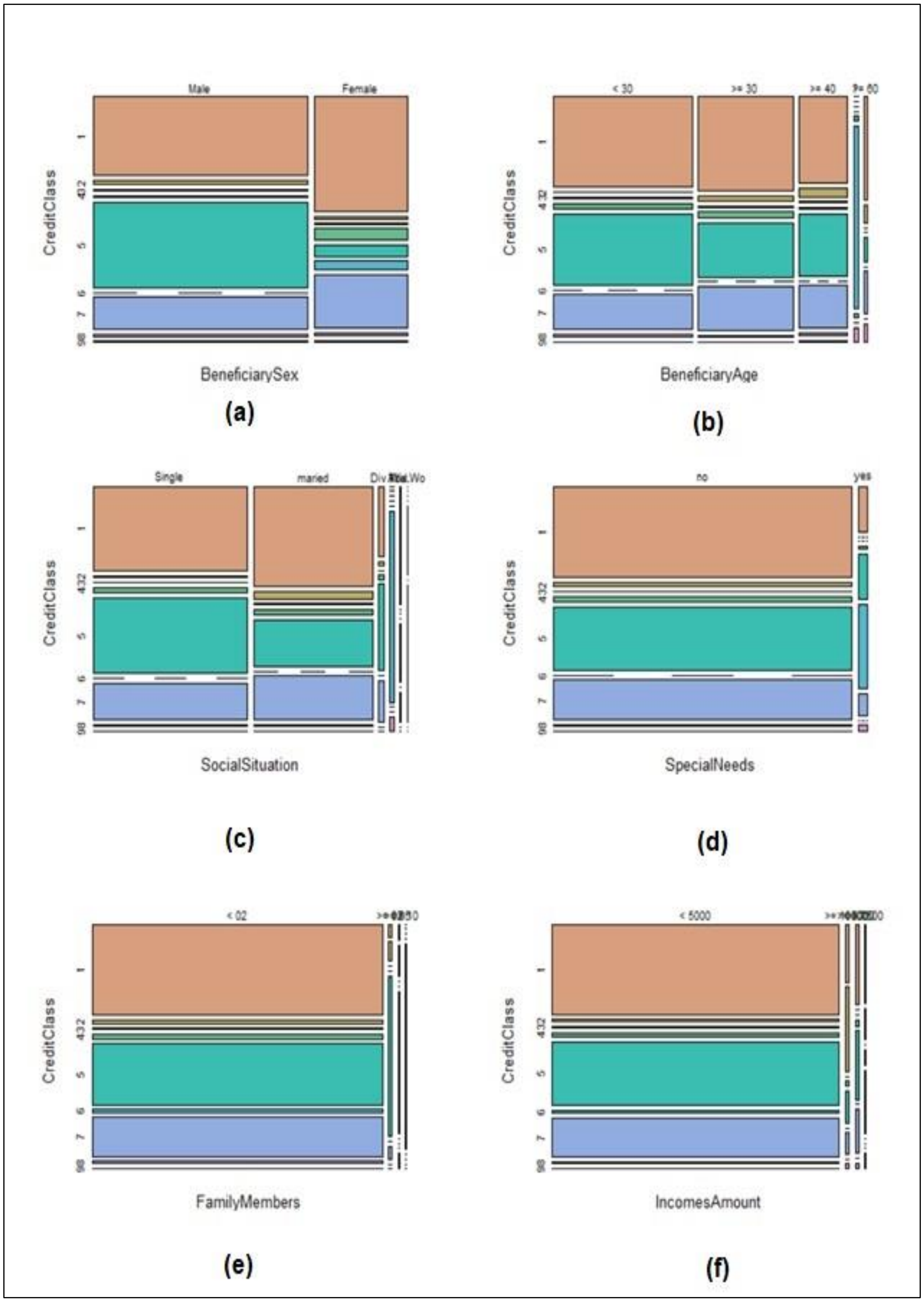


Figure 8

Bivariate analysis of business loans characteristics by credit class for the year 2020.



5. A Study of Main Characteristics of Social Loans and Their Beneficiaries Before and During the COVID-19 Pandemic Using Decision Trees

This study aims to build main characteristics (profiling) of the beneficiaries of each credit category by using decision trees. In this section, we give a brief description of decision trees. Afterwards, we present the best obtained trees and the different interpretations and discussions of main credit characteristics.

5.1. Decision Tree: a machine-learning model to solve complex classification problems.

A decision tree is a reliable and effective machine learning and data mining technique that provides high classification accuracy with a simple representation of gathered knowledge (Sathyadevan and Nail, 2015). The decision tree consists in a set of nodes that form a rooted tree. It begins from a node called "root" with no incoming edges while the other nodes have exactly one incoming edge. A node with outgoing edges is called test node while the others are called leaves. The leaves nodes are considered terminal nodes representing the most appropriate target values (classes). In a decision tree, each test node splits the instance space into two or more sub-spaces according to a certain discrete function of the input attributes values. Instances are classified by navigating them from the root of the tree down to a leaf, according to the outcome of the tests along the path.

Several decision tree algorithms were proposed in the literature such as ID3 (Quinlan, 1986), C4.5 (Quinlan, 1996), Random Forest (Rajesh and Chandrasekar, 2019) and many others. Among these algorithms, ID3 is considered the basic one which can only deal with categoric data (Chaabane et al, 2020). Quinlan solved this problem and proposed C4.5, also known as J48, which is a tree-based classification algorithm extending ID3 algorithm to deal with both categoric and numeric data. It uses the gain ratio for building the tree by dividing the values of a numeric continuous attribute in two subsets. Another well-known decision tree algorithm is the Random Forest, which builds random trees from a given dataset. Random Forest combines multiple decision trees which are merged for a more accurate classification. Random Forest is based on the idea that multiple uncorrelated models perform much better as a group than they do alone. When using Random Forest for classification, each tree gives a classification considered as a “vote.” The forest chooses the classification with the majority of the “votes.”

Given the simplicity and the interpretability of decision trees, they are used in a wide range of industries and disciplines such as in healthcare industries (Saraswat and Singh, 2020; Teixeira et al., 2013) and in the banking sector (Bhatore et al., 2020; Alex et al., 2018; Devi et al., 2017).In healthcare industries, decision trees can tell whether a patient is suffering from a disease or not based on conditions such as age, weight, sex and other factors. In the banking sector, decision trees are usually used to decide if a person is eligible for a loan or not based on his financial status, family member, salary, etc. Other applications may include credit card frauds (Alex et al., 2018), bank schemes and offers (Ozgur et al., 2021), loan defaults (Bhatore et al., 2020) which can be prevented by using a proper decision tree. We show in the next section how decision trees are used to build profiles of the beneficiaries of each credit category.

5.2. Experiments Design and Empirical Results

We performed two multivariate analyses on individuals and business microcredits separately before and during the COVID-19 pandemic. We considered the year 2019 as the period before the COVID-19 pandemic while the year 2020 as the period during the COVID19 pandemic. We modeled the profiling process as a classification problem by considering credit categories as the desired classes that can be solved using a machine learning decision tree. Most important characteristics of each credit class can be interpreted from the tree by describing most important paths towards the leaves of the tree representing each credit class. In order to build the best decision tree model for individual and business credits, we evaluated three types of algorithms for the years 2019 and 2020 separately. The evaluated machine learning algorithms are J48 (Quinlan, 1996), J48 Consolidated (Igor et al, 2015) and REPTree (Weka, 2021) with a maximum depth equal to 7 for all algorithms. This limit is configured to make the tree interpretable in visualization. The objective is to determine the best tree in terms of classification error which gives visual profiles of the beneficiaries of social loans. Table 5 reports the best obtained classification errors for each evaluated algorithm for the years 2019 and 2020. This table shows that there is no algorithm that outperforms the others on all datasets and for all years despite the good result of the consolidated J48 algorithm. In the following, we discuss the best obtained decision trees for each period and for each credit class.

Table 5

Best obtained classification errors for each classification algorithm for the years 2019 and 2020 respectively by using cross validation (10 times).

Credit Type	Year	Algorithm	Minimal Classification Error
Individual	2019	J48	21.45 %
		J48 Cons.	**21.07 %**
		REPTree	22.85 %
	2020	J48	22.45 %
		J48 Cons.	**21.37 %**
		REPTree	22.56 %
Business	2019	J48	25.45 %
		J48 Cons.	**24.37 %**
		REPTree	24.56 %
	2020	J48	24.89 %
		J48 Cons.	25.15 %
		REPTree	**24.16 %**

5.3.Social and Microloans Accorded for Individuals

Figure 9 and Figure 10 report the best obtained trees in terms of classification errors for the years 2019 and 2020 respectively.

Figure 9

Decision tree of main characteristics of individual loans for the year 2019.

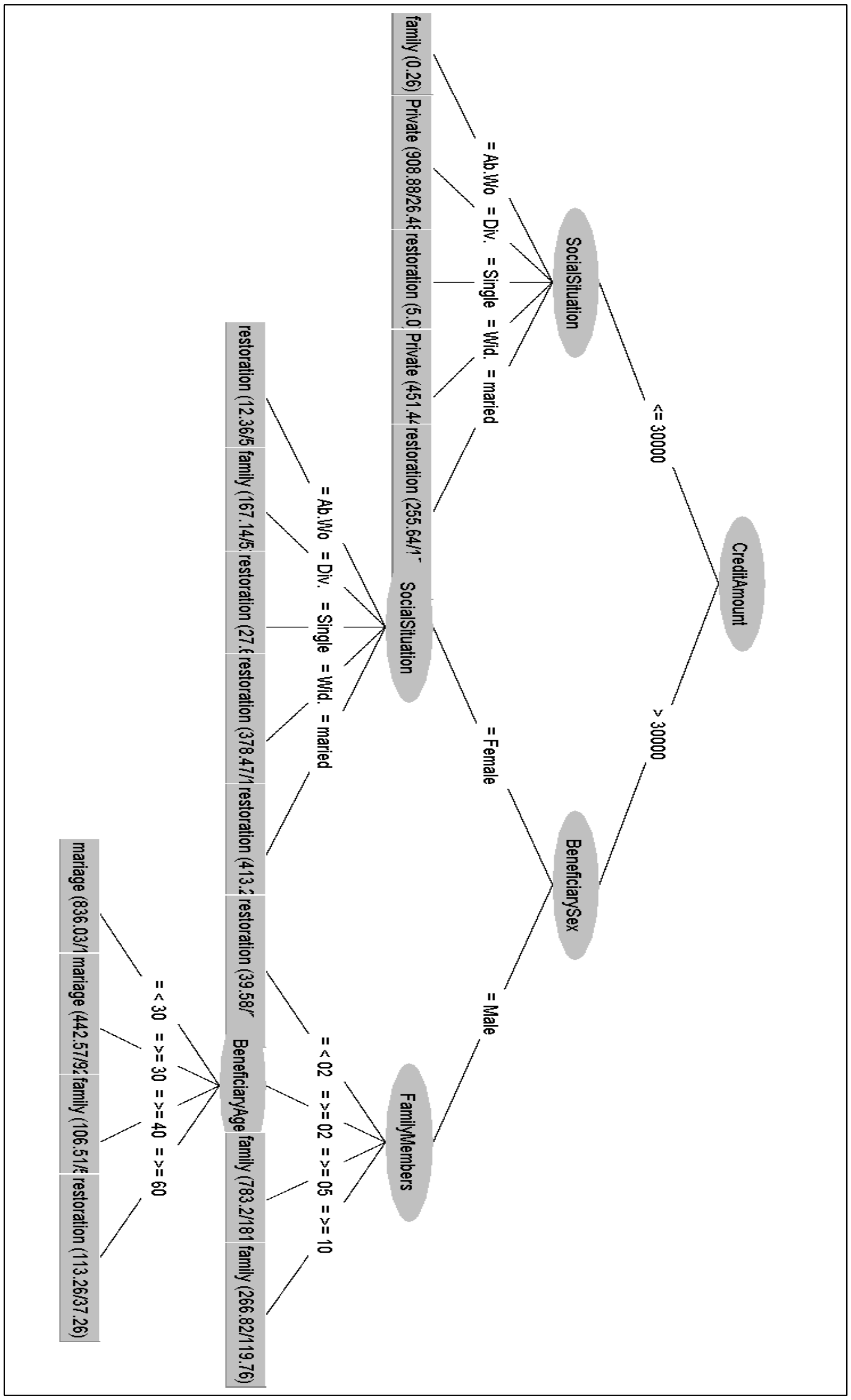
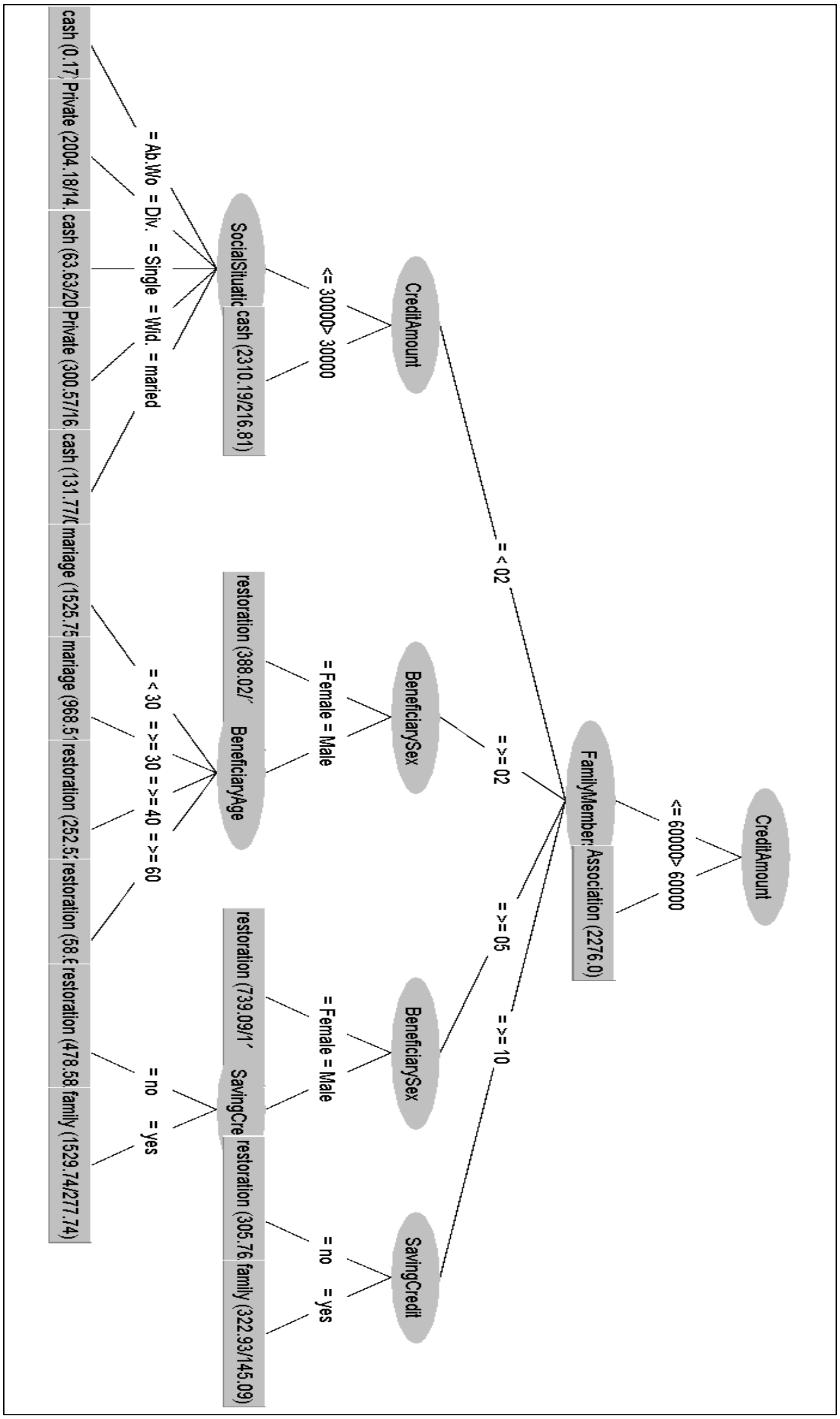


Figure 9 shows that, before the COVID-19 pandemic (year 2019), most of the beneficiaries having a social situation ‘divorced’ and ‘widower’ have benefited from the category of loans ‘private’. These credits do not exceed 30,000 SAR. Concerning the category of credit ‘restoration’, we show that most beneficiaries were married or had a number of family members more than two or old men aged over 60 or divorced and widowed women. Concerning ‘family’ loans, we show that beneficiaries were divorced women with a large number of family members (over 5) or married couples aged between 40 and 60. The last type of credit, ‘marriage’, most beneficiaries were men aged under 40.

Figure 10

Decision tree of main characteristics of individual loans for the year 2020.



Concerning the period during the COVID-19 pandemic (year 2020), we show in Figure 10 a new class of microcredit ('associative') which is characterized by a large credit amount exceeding 60,000 SAR. Concerning the category of credit 'private', we do not show any change of the beneficiaries' characteristics compared to 2019. Most of the beneficiaries have a social situation 'widower' or 'divorced'. For 'restoration', we show that most of the beneficiaries of this type of credit are women having a small family member or men aged between 40 and 60 without any engagement in any saving program with the bank. However, we show that for 'family' credits most of the beneficiaries are engaged in a saving program with the bank and have a large number of family members.

5.4. Social and Microloans Accorded for Business

Figures 11 and 12 report the best obtained trees in terms of classification errors for the years 2019 and 2020 respectively. Figure 11 shows that in 2019 most of 'emerging projects' credits were between 100,000 and 300,000 SAR while a little part of this category of credits had an amount under 100,000 SAR benefited from single and married people or people aged under 30. Concerning 'graduate program' and 'excellence' credits, we show that these credits are characterized by their high amounts compared to other credits categories, exceeding 500,000 SAR for the category 'excellence' and between 300,000 and 500,000 SAR for the category 'graduate program'. However, other categories, such as 'Private CAB', have an amount that does not exceed 100,000 SAR mostly benefited from single people or married couples aged over 40.

Concerning the period during COVID-19 pandemic, Figure 12 shows that the credit category ‘emerging projects’ has the same characteristics noticed during the year 2019. The credit amounts of this category were mostly between 100,000 and 300,000 SAR with fewer credits that have an amount under 100,000 SAR. For the categories ‘graduate projects’ and ‘excellence’, we show that most of these microcredits have a large amount compared to other categories (more than 300,000 SAR). The main shown difference between these two categories of credit is that most of the beneficiaries of ‘graduate projects’ were males aged under 40 while for the category ‘excellence’ most of the beneficiaries were males aged over 40. Compared to the period before the COVID-19 pandemic, we show a new category of credit ‘Quaem’ characterized by high credit amounts (over 300,000 SAR) and mostly benefited from special needs individuals.

Figure 11

Decision tree of main characteristics of business loans for the year 2019.

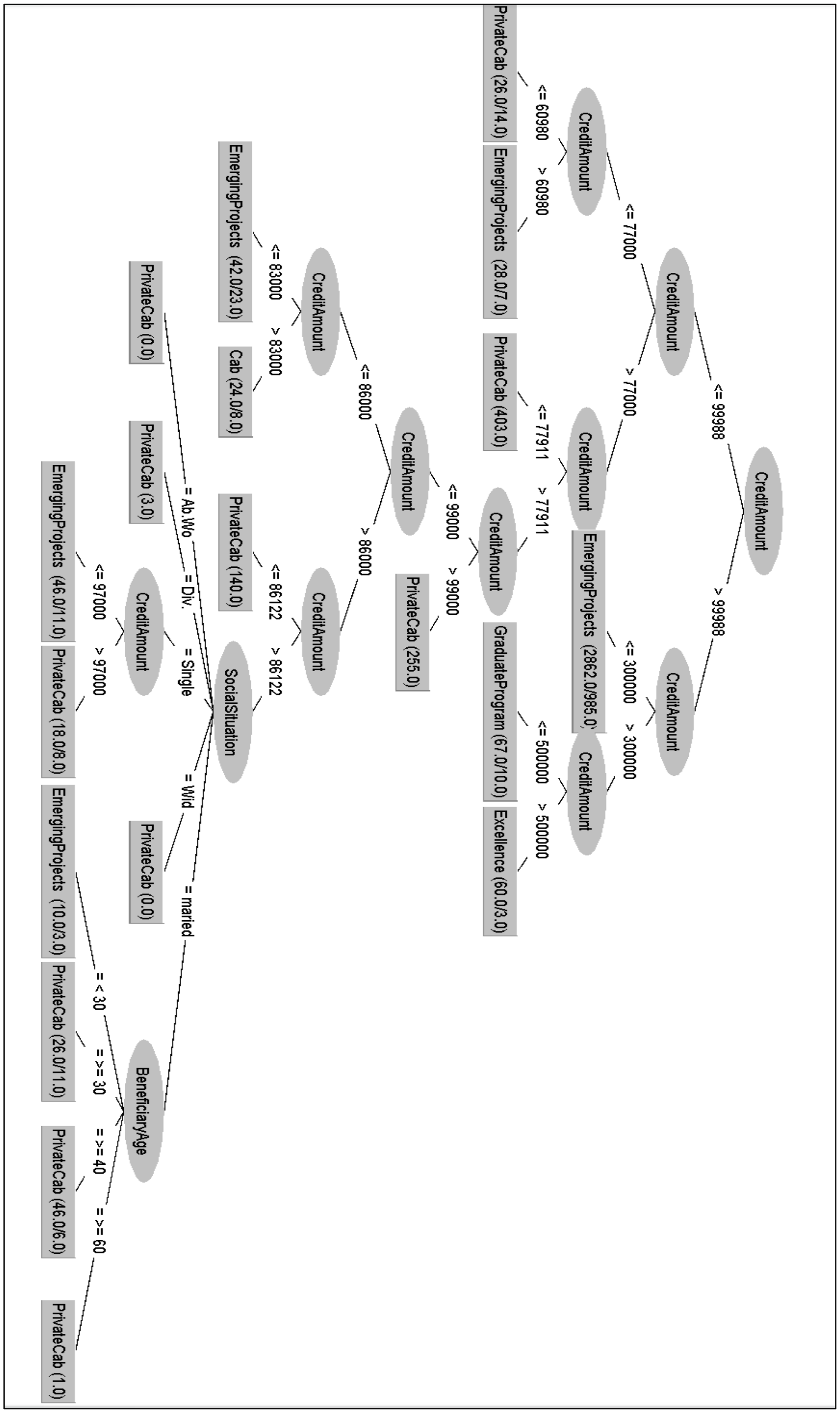
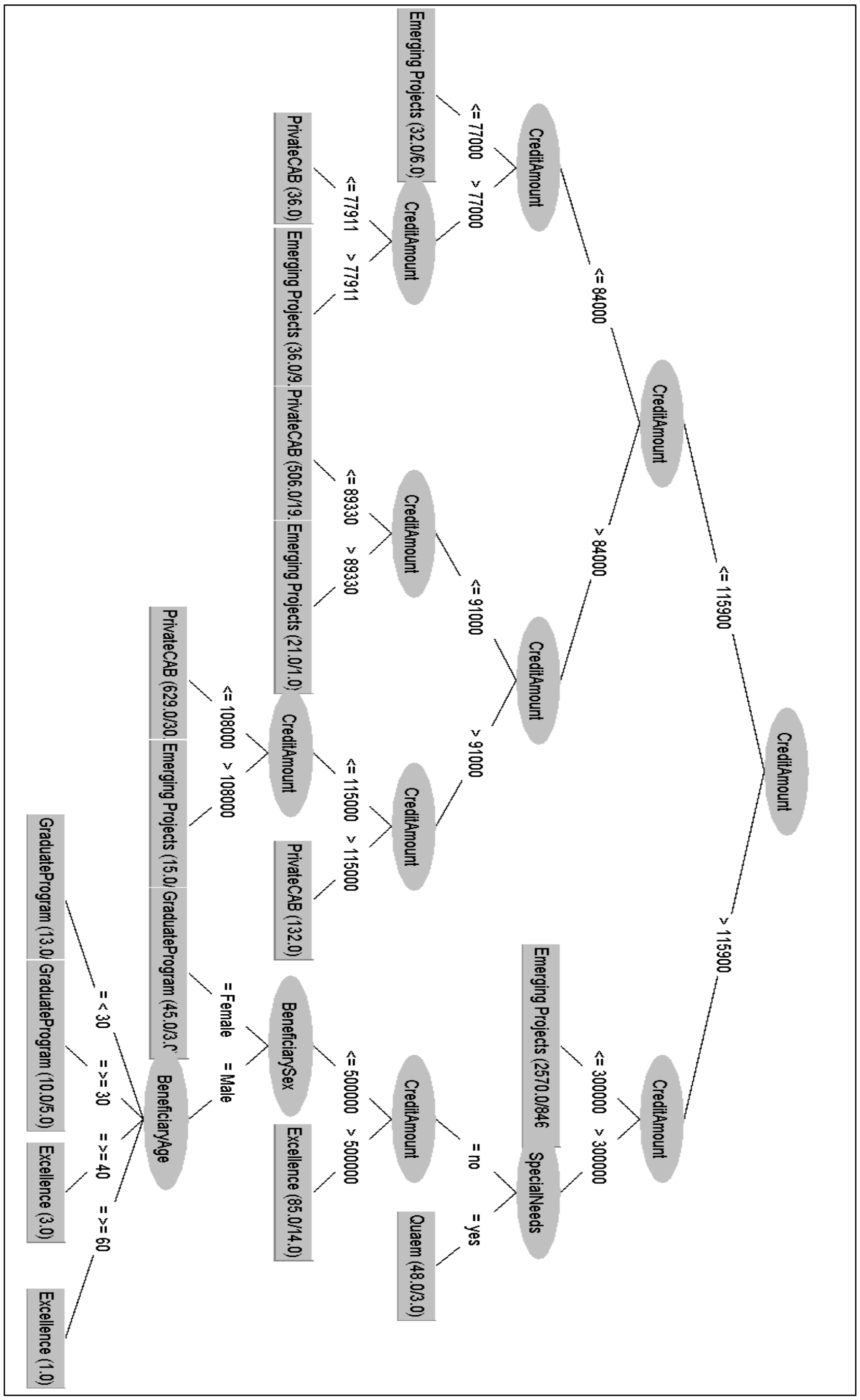


Figure 12

Decision tree of main characteristics of business loans for the year 2020.



6. Conclusion and Perspectives

We presented in this paper a study on social and microfinance credits in Saudi Arabia. We empirically analyzed the social and microfinance loans provided by the SDB during the last five years to support individuals and small business enterprises. First, this study showed the important growth of both individual and business credits for the year 2020, compared to the four previous years in terms of number and value despite the low oil prices and the disruptive effects of the COVID-19 pandemic. Second, our univariate analysis of the main characteristics of loans and their beneficiaries has showed a remarkable evolution of loans granted to women and the significant evolution of loans granted to special needs individuals. This fact can be explained by the government policy through the efficient reforms of Vision 2030 that encourage all governmental organizations to offer several facilities for these two segments of the society and to help them to integrate the economic life and to build a financial independence. After that, our study put emphasis on the repercussions of the COVID-19 pandemic on social loans. By using decision trees, we built main characteristics of microloans and their beneficiaries before and during the COVID-19 pandemic for individual and business credits. We discussed main changes in demographic, social and economic characteristics of the beneficiaries of each credit class separately. The obtained results will help managers to design more suitable and effective microfinance products.

Our study of social and microfinance credits is mainly based on the loans granted by the SDB. However, other non-banking financial institutions, accredited by the Saudi Central Bank, play a very important role in supporting Saudi men and women and in supporting small and medium-sized enterprises. An interesting way to improve this study is to extend the analysis of social credits and their beneficiaries to the loans granted by these micro financial firms. Another interesting way to improve this study is to include quality service variables in order to evaluate the quality of services and the facilities that social banks offer for the beneficiaries. This will put emphasis on new digital microfinance platforms, such as Tamam, and its important role in increasing the number of consumers benefiting from micro-financing services.

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