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Risk assessment when granting credit to non-financial legal entities

Evaluación de riesgos en la concesión de crédito por personas jurídicas no financieras

Avaliação de risco na concessão de crédito por pessoa jurídica não financeira

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Abstract

Purpose: This study aimed to verify risk assessment procedures when granting credit by a legal entity via financing in negotiations with its customers.

Methodology: A documentary approach was used, emphasizing qualitative analysis, during the experimental study conducted at an XYZ organization linked to information technology.

Results: They point out that the credit score and rating score, established through the evaluation stages, taking into account the company's history, documentation, guarantees, financial health, cash flow, indebtedness, corporate governance, and market prospects, enable the risk classification of their analyzed clients, ranging from AAA for the "alpha" client to D for the "beta" client. This result made it possible to deduce that credit assessment is appropriate automation in financing decisions for commercial activities, capable of promoting financial flexibility and commercial agility. Customer risk classification is therefore seen as a fundamental tool for improving XYZ's financial decisions, minimizing default risks, and guaranteeing the financial security of its commercial operations, resulting from establishing risk scores for both defaulting and non-defaulting companies.

Contributions of the Study: This study makes a relevant theoretical contribution to the field of research by highlighting the importance of validating the criteria used in granting financing, as well as the contextual factors that can affect decisions. The practical contribution of analyzing a non-financial institution under the pandemic context and how they minimize their default by establishing credit analysis mechanisms provides improvements and consequently greater security as lenders.

Keywords: Credit assessment for legal entities, default, credit score, rating score.

Resumen

Objetivo: Este estudio tiene como objetivo verificar los procedimientos de evaluación de riesgos en la concesión de crédito por parte de una persona jurídica, vía financiación, en las negociaciones con sus clientes.

Metodología: Durante el estudio experimental realizado en una organización XYZ vinculada a las tecnologías de la información se utilizó un enfoque documental, haciendo hincapié en el análisis cualitativo.

Resultados: Señalan que la nota de crédito y la nota de calificación, establecidas a través de las etapas de evaluación, teniendo en cuenta el historial de la empresa, la documentación, las garantías, la salud financiera, el flujo de caja, el endeudamiento, el gobierno corporativo y las perspectivas de mercado, permiten la clasificación de riesgo de sus clientes analizados, que van desde AAA para el cliente "alfa" hasta D para el cliente "beta". Este resultado permitió deducir que la evaluación del crédito es una automatización adecuada en las decisiones de financiación de las actividades comerciales, capaz de promover la flexibilidad financiera y la agilidad comercial. La clasificación del riesgo del cliente se considera, por tanto, una herramienta fundamental para mejorar las decisiones financieras de XYZ, minimizar los riesgos de impago y garantizar la seguridad financiera de sus operaciones comerciales, resultante del establecimiento de puntuaciones de riesgo tanto para las empresas morosas como para las no morosas.

Contribuciones del estudio: Este estudio realiza un aporte teórico relevante al campo de la investigación al resaltar la importancia de validar los criterios utilizados en el otorgamiento de financiamiento, así como los factores contextuales que pueden afectar las decisiones. El aporte práctico a la hora de analizar una institución no financiera, incluso en el contexto de pandemia, y la forma en que minimizan su morosidad estableciendo mecanismos de análisis crediticio, proporciona mejoras y consecuentemente mayor seguridad como entidades acreedoras.

Palabras clave: Evaluación del crédito empresarial, impago, puntuación crediticia, calificación crediticia.

Resumo

Objetivo: Este estudo teve por objetivo verificar os procedimentos de avaliação de risco na concessão de crédito por uma pessoa jurídica, via financiamento, nas negociações com seus clientes.

Metodologia: Empregou-se uma abordagem documental, com ênfase na análise qualitativa, durante o estudo experimental conduzido em uma entidade XYZ ligada à tecnologia de informação.

Resultados: Apontam que o *credit score* e o *rating score*, constituídos por meio das etapas de avaliação, considerando o histórico da empresa, documentações, garantias, saúde financeira, fluxo de caixa, endividamento, governança corporativa e perspectivas de mercado, possibilitam a classificação de risco aos seus clientes analisados, variando de AAA para o cliente "*alpha*" e D para o "*beta*". Tal resultado possibilitou deduzir que a avaliação creditícia, oportuna automatização nas decisões de financiamento das atividades comerciais, capaz de promover flexibilidade financeira e agilidade comercial. A classificação de risco dos clientes é vista, portanto, como uma ferramenta fundamental para aprimorar as decisões financeiras da empresa XYZ, minimizando riscos de inadimplência e garantindo a segurança financeira de suas operações comerciais, resultante do estabelecimento de pontuações de riscos, tanto de empresas adimplentes quanto das inadimplentes.

Contribuições do Estudo: Este estudo traz uma contribuição teórica relevante para o campo de pesquisa ao destacar a importância de validar os critérios usados na concessão de financiamento, assim como os fatores contextuais que podem afetar as decisões. A contribuição prática ao analisar uma instituição não financeira, inclusive sob o contexto pandêmico, e a forma com que elas minimizam sua inadimplência ao estabelecer mecanismos de análise de crédito, proporciona melhorias e consequentemente maior segurança como entidades credoras.

Palavras-chave: Avaliação de crédito por pessoa jurídica, inadimplência, *credit score*, *rating score*.

1 Introduction

The search for credit from financial institutions in 2020 and 2021 has been significant, according to the Central Bank's report, which points out that the balance of credit operations in the National Financial System reached R$4 trillion in 2020 (an increase of 15.5% compared to 2019) and R$4.7 trillion in 2021 (an increase of 17.5% compared to 2020). Free credit for legal entities reached R$1.1 trillion in 2020 (an increase of 14.1% compared to 2019) and R$1.3 trillion in 2021 (an expansion of 18.2% compared to 2020). The main reasons for this growth were the increase in the types of trade bills and advance payment of card invoices (BACEN, 2021; BACEN, 2022).

Other relevant data pointed to a general average interest rate for contracts in 2021 of around 24.4% p.a. (32.6% higher than 2020), with free credit closing the same year at 33.9% p.a., under a default rate of 3.1%, unlike in 2020 where there were reductions in the level of arrears among legal entities (-0.9 p.p.), partially influenced by debt renegotiations and extensions resulting from the context of the pandemic (BACEN, 2021; BACEN, 2022).

Although there are still no concrete studies on the effects on the financial market of credits incurred during the COVID-19 pandemic, including by lending companies in non-financial sectors in emerging countries, it is possible to associate risks with the dynamics assisted in bank loans (Goodell, 2020). In this context, Gong, Jiang and Le (2021), using a sample of 37 countries during the H1N1 pandemic in 2009-2010, with institutions that made bank loans, observed that the pandemic increased the cost of funding and at the same time restricts the volume of bank loans due to the perceived risks between the parties (borrower and bank).

On the other hand, the severe economic slowdown caused by the pandemic is expected to result in high levels of indebtedness, which could increase company and family defaults. This will occur until economic policy, especially monetary policy, is adjusted to accommodate and mitigate the impact of rising unemployment and declining company profitability, as it fears the outbreak and cycle of rising debts (Park & Shin, 2021).

From the point of view of corporate borrowing, the pandemic has caused a sudden and exogenous increase in risk for financial institutions, i.e., banks. Although banks are more likely to lend in this scenario, some studies have concluded that the pandemic leads to a decrease rather than an increase in credit despite unprecedented government stimulus efforts and cash injections aimed at preventing interruptions in the supply of credit (Çolak & Öztekin, 2021).

The conjecture and motivation behind this study are that, due to the pandemic, many companies have had their need for working capital increased for a series of reasons inherent to their economic activity and have, therefore, needed quick cash to pay employees, suppliers, and other creditors, in order to keep their activities going, that is, adapting to reality with immediate liquidity adjustments.

However, companies (legal entities) have taken out loans or financing at high-interest rates as a circumstantial mechanism to preserve liquidity. This has been more common in segments susceptible to the state of the local and global economy, such as restaurants, bars, hotels, airlines, and tourist agencies. Although demand in these sectors has been affected, efficient working capital management should, in principle, allow business to continue. However, on some occasions, raising funds has become unavoidable.

With this in mind, the question is: **"How did non-financial institutions meet the demand for financial credit with risk assessment practices in their concessions that did not lead to an increase in defaults?"** To answer this question, it is known that financial institutions are willing to provide resources with short or long-term loans. However, it is also known that these institutions and the National Financial System value safety in granting loans so that the economy and the institution are safe and stable for the market to function, but what about non-financial companies? (Silva, Carvalho Neto & Souza, 2021).

This is because every credit operation is exposed to the risk of default. When granting credit, the governing bodies must identify it and be aware that it will directly impact the lender's financial results if the borrower fails to meet their obligations (Securato & Famá, 1997).

Therefore, risk exposure implies the possibility of default, which, although it represents the possibility of the bank earning more income on the amount owed and not paid, it is estimated that the debtor agent may also not be able to settle the debt, which would therefore increase the banking *spread,* making the cost of capital more expensive for future concessions. In other words, banks aim to adopt actions (credit analysis) to preserve their liquidity and inhibit non-payment of loans made on time.

In this context, in favor of risk analysis in bank loan portfolios for legal entities to reduce default risks, this article aims to highlight the use of credit analysis by non-financial legal entities, seeking to understand the dynamics of granting credit. As such, loan procedures that took place during COVID-19 will be evaluated, as this way, the analysis will be carried out under circumstances where stricter criteria are assumed due to the risks involved in this pandemic period.

The justification for carrying out this study stems from the practical contribution made by analyzing a non-financial institution in the context of the pandemic and how it minimizes default in its negotiations with borrowing clients and admitting the relevance of validating the criteria used in granting a loan, by adding circumstantial analyses that can also serve as decision-making elements. In this way, it can improve analysis and, consequently, greater security for lenders, making sense of the theoretical contribution by highlighting the importance of validating criteria in granting financing as risk factors that affect financing decisions.

2 Literature review

2.1 Credit risk

The word credit has its origins in the Latin word *credere*, or even from the noun *credit*, which means trust, and also in an understanding of banking relationships (credits obtained from financial institutions), as discussed in Ashofteh and Bravo (2021), Das, Kalimipalli and Nayak (2022), Kavussanos and Tsouknidis (2016), and Santos (2003), who state that it consists of a certain amount being made available to the client in the form of a loan or financing with the promise of payment at a future date.

In the context of this study, the granting of credit refers to operations in which a person or company obtains a monetary resource from a third party, assuming the commitment to pay the amount in the future plus interest and charges (Das et al., 2022; Silva et al., 2021; Santos, 2003).

Preliminarily, financial institutions use the 5 "Cs" of credit analysis as a basis: character, capacity, capital, collateral and conditions to assess the feasibility of granting a loan. Although these aspects lack a more robust analysis, they still need to be capable of reflecting the actual economic situation of the borrower, which weakens concessions without much rigor in analysis (Carvalho *et al.*, 2014; Neoway, 2021; Santos, 2003)

A credit analysis's 'character' aspect has been understood as an assessment of the borrower's payment history. In this context, the fulfillment of financial commitments made to the intended institution and those previously made are investigated. This can be analyzed by looking at deadlines, defaults and debts incurred. This investigation is carried out through the borrower's history and external sources, such as consultations with credit protection agencies such as Bacen and Serasa. As for the 'capacity' aspect, this concerns compliance with what has been agreed, i.e., the individual's 'purchasing' power demonstrated through their financial statements about what has actually been borrowed and paid back (Neoway, 2021).

In other words, the fact that it is liquidated can also be analyzed, as it may be due to liquidation by a notary's protest, for example. In addition, the time on the market, cash flow, and projections are also observed as components of the capacity or solvency ratio.

In addition to the preliminary analysis of the "Cs", there is also "capital", which analyzes how financially sound the borrower is. The purpose is to guide profitability, investment power, debt ratio, etc. In terms of 'collateral', this "c" relates to what the client leaves as a guarantee that they will not fail in their financial responsibilities. Examples of this are real estate, valuable items, vehicles, etc. Finally, the 'conditions' aspect, in which the assessment refers to the need to identify the economic context in which the bidder is inserted, together with their payment conditions and the market outlook (Neoway, 2021).

For Santos (2003, p. 46), the "Cs" represent "subjective analysis, or case-by-case analysis, based on the experience acquired by credit analysts, technical knowledge, common sense and the availability of information (internal and external) that enables them to diagnose whether the client is suitable and can generate revenue to honor the payment of loan installments."

However, loans are one of the primary forms of financing in a wide range of economic sectors, and lending institutions have played an essential role in supporting industrial, agricultural, commercial and service companies. Even if the analysis is detailed, there is still a credit risk that can lead to default, usually caused by various factors. In the study by Kavussanos and Tsouknidis (2016), they found that specific variables in the banking sector attributed current and expected circumstances, including the desire for default risk, to the possibilities of issuing loans.

According to Gouvêa, Gonçalves and Mantovani (2015), credit granting activities represent an essential role for banks, whose credit risk conditions the composition of institutional risk, requiring safe observance when issuing funds to customers, in cases, for example, of bank credit which includes: loans, financing, discounted securities, deposits, foreign exchange, leasing business, guarantee of sureties, etc. Understanding them conceptually helps guide default management and mitigation.

Another point is that there is a *trade-off* between the needs of borrowers and the latent and unavoidable risks implied by creditors. One of the ways banks and financial institutions have found to minimize this dilemma is by adopting *credit scoring* to assess the credibility of their customers (Dahooie *et al.*, 2021).

If, on the one hand, assessing customers' ability to pay before lending is one of the most critical challenges for improving the banking system, on the other hand, it has to be considered whether rigorous and conservative credit assessment will deprive eligible companies of access to their necessary financial resources (Dekkers *et al.*, 2020).

Since then, various methods have emerged to evaluate credit performance. Some of these methods are statistical and mathematical, such as support vector machines (Zhang et al., 2014), discriminant analysis by decision trees (Altman, 1968) and logistic regression (Lee *et al.*, 2006), while others rely on artificial intelligence, such as inductive learning (Han et al., 1996), artificial neural networks (Akkoç, 2012), genetic algorithms (Kozeny, 2015), among others. If combined with data verification technologies, many of these methods can improve the identification of borrowers with their ability to pay. For example, in the credit analysis for small and medium-sized retailers, variables can be associated with the traffic data of people in stores and internet users on virtual sales channels (Schiozer & Yoshida, 2020). In short, many models can be built, and it is up to credit analysts to have a good credit policy at their disposal with tools that make the analysis more accurate for decision-making.

According to Santos (2008, p. 14), in credit risk management, "there are countless methodologies for identifying clients in terms of their ability or inability to honor their commitments to creditors" (i.e., assessing possible creditworthiness and insolvency), which are not equally effective. For the author, quantitative analysis must complement a more refined qualitative analysis. So that credit analysts can obtain as much information as possible for decision-making.

A joint quantitative and qualitative analysis can better ascertain the risk classification. However, from the perspective of a risk classification anchored solely to the Central Bank database, this can be flawed, as it weights overdue transactions (i.e., defaults) and is not the cause of the delay. It is, therefore, necessary to add to the analysis of defaults an understanding of or information on the complementary causes since these can influence unfavorable decisions with clients who have commercial potential for doing business with the credit concessionaire. What is more, if you consider the risk rating of a particular bank as a parameter, this resource also lacks information to better guide decision-making because, in addition to the cadastral, financial, asset, sectoral, macroeconomic and suitability analysis, it is necessary to consider the contribution of insolvency prediction models (Santos, 2008, p. 14).

2.2 Individual Microentrepreneurs and Small Businesses

An individual micro-entrepreneur (MEI) is a simplified way of formalizing an individual business with gross revenue of up to R$ 81,000.00 per year (considered for the year 2023), with the option of Simples Nacional and exemption from registration fees, taxes, and others. In short, to be an MEI, you need to have a turnover of up to R$ 81,000.00, not be a partner, administrator or owner of another company, not have more than one employee, carry out one of the activities allowed by Simples Nacional and not be a pensioner, federal civil servant or military officer (Receita Federal do Brasil, 2023).

Simples Nacional is a simplified tax system created by the Federal Government to make it easier for micro and small companies, individual entrepreneurs and micro-entrepreneurs to pay taxes. It aims to simplify the administration of taxes for these companies, allowing them to pay everything in a single form, which includes various taxes, such as Income Tax, CSLL, PIS, COFINS, IPI, ICMS and ISS, and with, in most cases, reduced rates (Receita Federal do Brasil, 2023).

According to data from the Entrepreneur Portal, from January to November 2021, the number of MEI companies opened in Brazil was approximately 1.4 million. The number of MEI companies closed in the same period was approximately 654,000. Another relevant fact is that of the micro-enterprises opened, 46.71% were closed in less than five years, from 2017 to 2021 (Portal do Empreendedor, 2022).

It is worth pointing out that these figures can vary depending on various factors, such as the economic situation, public policies to encourage entrepreneurship and the pandemic. In addition, it is understood that the success of an MEI venture depends not only on formalization but also on other aspects, such as business management and the individual's entrepreneurial capacity.

According to a Micro and Small Business Support Service survey, 59% of small businesses (including MEIs) were in debt in 2020 (SEBRAE, 2022). The main factors that led to this indebtedness were the drop in turnover due to the COVID-19 pandemic, which was offset by increased loans and financing to maintain cash flow to pay suppliers and employees.

2.3 Credit concessions in the COVID-19 pandemic

During the COVID-19 pandemic, concerns arose about the possible worsening of the financial system, in which banks were subject to *default* situations (i.e., non-compliance with credit agreements, which would lead to the triggering of defaults). In other words, loans between countries or private entities, such as companies and financial institutions, are susceptible to default. In this perspective, investment tends to decrease, and corporate defaults increase, negatively affecting working capital factors in the economic system, forming a situation that can get out of hand: the lack of liquidity and systemic risk can quickly evolve into widespread insolvencies (Ramos-Francia & García-Verdú, 2022).

An emergency way to remedy the possible pandemic effect on the financial system was through the interventions of central banks, seeking to find an effective balance in mitigating the risks mentioned above. According to Ramos-Francia and García-Verdú (2022), the central banks' objectives were basically: i) to avoid a systemic crisis; ii) to promote economic recovery. According to the authors, central banks had two intermediate objectives: 1) the provision of liquidity and 2) the viability of credit channels.

By the beginning of October 2022, Brazil was the third country most severely affected by the pandemic in the world, after the USA and India, where the number of new cases and deaths continued to rise, reaching levels of 34.6 million confirmed cases and 686,320 deaths (Agência Brasil, 2022; Who, 2022).

From the perspective of the Brazilian credit market, it is characterized by high-interest rates, a high risk of creditor (borrower) default, a relatively weak legal environment with overloaded courts, and low oversight (Ponce, 2020). However, under pandemic circumstances, a study carried out in Brazil by Acharya and Steffen (2020) in the initial phase revealed that even with the necessary institutional and political interventions, local credit was negatively affected by the severity of COVID-19. The authors also revealed evidence of large companies taking advantage of existing credit lines at the pandemic's start for precautionary reasons.

In Brazil, it was found that lending during the pandemic was concentrated in the largest banks (Norden et al., 2021), regardless of the level of relationship with the lending institution. Moreover, even with significant resources available to lend, creditor institutions obtained low expected levels of loans due to the high-interest rates charged by commercial banks on contracts (Berger *et al.*, 2021). The credit market led by state-owned banks in Brazil grants relatively more credit than private banks, and when comparing the COVID-19 crisis to the 2008 *subprime* crisis, it was found that this current one was less cyclical, based on the year 2020. This effect can be explained by the different nature of the two crises, issues of banking governance and political influence on state banks and the recovery after the first wave of COVID-19 in Brazil (Berger *et al.*, 2021; Beck & Keil, 2022; Li et al., 2020; Norden et al., 2021).

A curious fact in the financial market during the pandemic in the United States is that banks experienced a significant increase in their deposits, reaching around US$ 1 trillion in the year 2020 (Li et al., 2020). This revealed that families had accumulated their savings in their deposit accounts as a result of a reduction in spending, i.e., they were unable to spend money on leisure activities due to mobility restrictions, known as forced savings. This led to a significant increase in bank deposits, and, in turn, banks used these additional resources to issue more real estate loans (Dursun-De et al., 2022).

On the other hand, although financial institutions had money available to lend, even considering the contribution made by the Central Bank to combat the adverse effects of COVID-19 on the financial system, where it allocated R$1.216 trillion for Brazilian banks to preserve liquidity with their customers, to carry out their operations with customers (individuals or companies) usually, the fear of default prevailed, and this caused many banks to be more prudent and rigorous in their risk analysis in their credit policies (BACEN, 2022).

Some data extracted from the Central Bank of Brazil's Financial Stability Report for 2022 indicated a total volume of bank loans in 2021 to households (legal entities and individuals) in the order of R$664 billion, making up an amount in the stock of credit already lent of R$4.6 trillion. In 2020, the volume was R$ 539.369 billion (and the amount of credit stock lent was R$ 4.02 trillion; i.e., in 2021, the growth was 16.5% higher). Also, in 2019 and 2018, the credit volumes granted by banks were R$213.413 billion and R$159.641 billion. Another relevant fact is that credit to individuals rose by 20.8% in 2021, compared to 11.2% in 2020. On the other hand, credit for legal entities decreased in 2021, growing by only 11.1%, compared to 21.8% in 2020 (BACEN, 2022).

It should be noted that, despite the need for credit during the pandemic, financial institutions reduced the amount of loans to legal entities in 2021. The average interest rate on loans in 2020 and 2021 was 18.3% and 24.3%, respectively, with increasing fluctuations, which in April 2022 rose to 27.7% p.a. (BACEN, 2022).

2.4 Default

Default is preliminarily understood as failing to fulfill an obligation (Houaiss & Villar, 2001). However, according to these authors, for an operational definition of default in credit risk assessment, as much as we try to associate it with the American terminology known as *default,* there is a polarity of understanding among analysts, as some tend to adopt stricter parameters in order to achieve a risk classification system that authenticates credit operations more moderately. On the other hand, some analysts focus on systematized criteria that parameterize possible deals that could be profitable for the financial institution.

Despite the plethora of concepts on the subject of default, the following understanding of default in the *stricto sensu sense was* accepted in this study, according to the postulates gathered in studies by Annibal (2009): it is the failure to pay a certain amount under the terms of the original credit operation contract.

Granting credit only to those who can pay is the most effective way of preventing default, but doing so is more complex (Sehn & Carlini Junior, 2007). The fact is that borrowers are subjected to credit analysis, and even so, financial institutions' default portfolios are significant (Serasa Experian, 2022a).

Regarding data, there was some variation in the growth and changes in default, considering the year 2020. For the first time in four years, there was a drop in the total number of Brazilians in default to 61.4 million, which is 3.1% less than in the same month of the previous year. This is the lowest figure since June 2018, when the total number of Brazilians in default was 61.2 million. This is due to financial institutions facilitating the renegotiation and extension of contracts due to the COVID-19 pandemic. On the other hand, records of families and individuals, through data provided by Serasa Experian (2022a), together with the reports of the Map of Default and Debt Renegotiation in Brazil, in the period from 2017 to 2021, revealed that the percentages of default have been increasing. The debt in March 2022 was R$263 billion, corresponding to the highest value recorded in the historical series of the last three years. In addition, the average amount of debt among Brazilian creditors is now R$4,046.31, equivalent to almost four minimum wages.

Based on data from the Consumer Indebtedness and Default Survey (CNC, 2022), considering only the months of August between 2008 and 2022, with an observation field on the percentage and number of families in debt and who have already stated that they are unable to pay, the following Table 01 was obtained:

Table 1

Changes in household indebtedness

Month/Year	Indebted Households (%)	Number of families unable to pay their debts
Aug/08	44,7	164.105
Aug/09	48,7	290.843
Aug/10	50,2	176.057
Aug/11	45,1	196.822
Aug/12	53,5	177.658
Aug/13	52,6	245.904
Aug/14	49,4	186.881

Aug/15	54,8	206.793
Aug/16	51,5	328.621
Aug/17	53,4	367.667
Aug/18	53,6	376.161
Aug/19	58,0	344.127
Aug/20	56,4	300.735
Aug/21	67,2	308.591
Aug/22	76,6	346.667

Source: *CNC, 2022.*

Although the contagion of the 2008 *subprime* crisis has resulted in a relative increase in volatility after the crisis, pointing to potential interdependencies and contagion effects in emerging economies, causing financial stress (Bianconi et al., 2013), Table 01 allows us to see some preliminary comparisons. It shows that, from 2008 to 2019 (one year before the COVID-19 pandemic crisis), the number of people in debt increased by 29.8%. If we look from 2008 to 2022, the increase was 71.4%. Between 2019 and 2022, the increase was 32.1%. Now that individual households are showing this behavior, it is expected to impact the consumer market since they are an integrated system between individual and corporate households.

From the same time perspective seen in Table 01, now considering the number of families unable to pay their debts, the percentage increase was 209.7% (i.e., around 180,000 families were incorporated as unable to honor their debts). Between 2008 and 2022, the variation was 211.2% (an increase of 183,000 families). From 2019 to 2022, the percentage increase was 7.4% (an increase of 2,540 families). It is understood that the compounding of all household indebtedness, to a certain extent, puts the companies' commitment to new loans at risk, especially given the magnitude and dispersion presented in circumstances of systemic crises.

Since 2008, banking regulations have been improved, and the changes have required banks to have a more significant capital base to withstand losses. It is said that default is a strong driver of macroeconomic imbalances, increasing the risk of financial operations in corporations and affecting the individual debtor's psychological, family and social situation (Schiozer & Yoshida, 2020).

3 Methodological procedures

3.1. Analysis of the Target Company (XYZ)

For empirical analysis, the lending company was XYZ (a fictitious name to preserve its identity). It operates in the Information Technology (IT) sector and has been experiencing growth in its business, generating employment even during the pandemic crisis. However, this is not a case study under protocol procedure. The company is accepted only as an analytical and observational element in its capacity as a credit supplier for realizing its business, whose possible and observational elements in the analysis of this study are under its creditor operations.

As a brief qualitative characterization of the company XYZ, it is known that it has been operating in the IT market for around 20 years, excels in transparency and commitment to its customers, and offers services and solutions in the technology area with a focus on optimizing results, reducing costs and competitiveness. It has extensive technical knowledge of Oracle Middleware products and technologies. Its objectives are structured as follows: (i) Business: to design, produce, integrate and manage complete *software* solutions for the corporate market; (ii) Mission: to make a difference for clients by delivering superior solutions that motivate and reward all stakeholders; (iii) Vision: to be recognized for its technical competence, capacity for innovation and commitment to clients in the markets served.

Its market is restricted to around 50 clients, and it offers an integrated portfolio of solutions and products combined with efficient services, project management and *software* development. The company specializes in the most popular market-leading *software,* with highly qualified and certified workers, offering various services, especially Oracle, Tableau, Salesforce and CA products.

With experience in engineering, *design* and development, the company is a consolidated *software* factory for the leading technologies such as Java and NET, with more than 30,000 hours of *software* development. It also offers services and solutions for collecting, managing and analyzing large amounts of information, enabling fast and effective decisions with its corporate data and *big data*. The company is also characterized by the following management information: a) small-sized company; c) company with a low-risk rating (*scoring)*; d) regular certificates with federal agencies; e) low financial dependency; f) no outstanding debts with REFIN (a Serasa service which allows debts to be settled and outstanding debts with banks and other financial institutions to be included); g) average monthly turnover of R$ 350.000.00; h) debt level of 9%; i) current and non-current liabilities of R$ 1,100,000.00.

Given this scenario, we can see from this preliminary information that the company has good financial stability, with no overdrafts on the market. However, it does not have a specific sector for analyzing its customers' credit, so it needs a detailed view of the company's financial results. As a result, debts incurred due to customer defaults increasing during the pandemic need to be correctly analyzed and mapped, including their influence on financial reports. The absence of this control can cause inconsistencies between actual cash and the cash estimated by the financial reports, which shows a possible financial scenario that is different from what is considered realistic and can worsen its working capital.

In this way, company XYZ is the one that is susceptible to credit analysis with its customers, and it is up to it to establish *scoring* criteria to relate to its customers. In this respect, criteria were accepted as steps for analyzing and granting credit. These are now analyzed in this study as viability, based on using a guide or manual with two of the company's "*alpha*" and "*beta"* clients. This experiment took place during the first half of 2022 to analyze the lending company's credit granting criteria. The identity of the clients was also preserved in this study.

This research used a qualitative approach to understand credit assessment, involving company XYZ and two of its clients in an experimental method. This method follows a systematic, six-step approach to granting credit efficiently and safely. The research begins with collecting customer data, encompassing general information and financial and behavioral history. This data is then analyzed, establishing risk classifications based on their profiles and ability to pay. This classification considers factors such as credit history, income, payment history and other financial indicators. Based on this classification, the company has made more informed and accurate decisions about granting credit, optimizing its resources and minimizing the risk of default.

Therefore, this study aims to demonstrate the benefits of setting up a credit analysis department, which favors its financial transactions and provides greater security for the company's capital.

3.2 Credit Granting Guidelines

In order to carry out a credit analysis in a company, it is prudent and necessary to describe a brief manual containing the administrative procedures necessary for the credit granting process. The function of a manual is to serve as a guideline for each stage of the process, providing all the necessary information, such as the assignment of responsibilities, requirements, a process flowchart and other measures inherent in the process. The manual should be drawn up based on the company's history of operations and the improvements that everyday life demands in the face of adverse situations. Based on the literature used to briefly draw up the manual (Dinh & Kleimeier, 2007; Kavussanos & Tsouknidis, 2016; Santos, 2003; Santos & Famá, 2007; Serasa Experian, 2022b), the following steps were considered necessary for analyzing and granting credit:

Step 1 - Credit assessment:

Responsible Agent: Credit Analyst.

Tools: system connected to the *credit score* (Serasa).

Criteria: a) compatibility between credit requested/commercial conditions; b) market situation; c) client's managerial skills; d) client's credit companies in the market; e) payment capacity, client's assets and guarantees; f) time in business and share capital; g) assessment of the risk involved; h) issuance of bad checks; i) outstanding financial debts with financial institutions; j) the company's share capital; k) companies belonging to the company should be analyzed together; l) classifying customers by consulting Serasa Experian, according to Figures 1 and 2, risk classes:

Risk	Risk Class	Range Score	Probability of Default		
			Minimum	Average	Maximum
Bass	A	89 to 100 (very high)	0.10%	1.80%	4.00%
	B	75 to 89 (high)	greater than 4.0%	7.00%	10.30%
Medium	C	57 to 75 (average)	greater than 10.3%	15.10%	20.70%
High	D	39 to 57 (bass)	greater than 20.7%	27.70%	35.40%
	E	24 to 39 (very low)	greater than 35.4%	43.00%	52.30%
	F	0 to 24 (critical)	greater than 52.3%	63.50%	98.80%

Figure 1 *Credit risk classes*
Source: *Serasa Experian, 2022b, adapted.*

Risk Class			Subjective Concept	or	Objective Concept
1	or	AAA	Minimal Risk		Probability of Default of 0.5%
2		AA	Low Risk		Probability of Default of 1.0%
3		A	Medium Risk		Probability of Default of 4.0%
4		BBB	High Risk 1		Probability of Default of 10.0%
5		BB	High Risk 2		Probability of Default of 15.0%
6		B	High Risk 3		Probability of Default of 20.0%
7		C	Imminent Default		Probability of Default of > 50.0%
8		D	Default		In default (in the company or on the market)

Figure 2 *Classes and Conceptualization of Credit Risks.*
Source: *Serasa Experian, 2022b, adapted.*

Step 2 - Granting credit:

Responsible: Credit Coordination.

Tools: system connected to the *credit score* (Serasa).

Criteria: Classification table 2 is shown below:

Table 2
Credit limit proposal approval criteria

Position	Clients WITHOUT guarantees or WITH insufficient guarantees (R$)	Clients WITH guarantees (R$)
Coordinator	0,00	800,00
Sales Manager	0,00	4.500,00
Country Manager	16.000,00	16.000,00
Director	25.000,00	25.000,00
Committee (all directors)	35.000,00	35.000,00
Superintendence	> 35.000,00	> 35.000,00

Source: *CNC, 2022.*

Step 3 - Credit limit management:

Responsible: Credit Coordination.

Tools: system connected to *Credit Score* (Serasa).

Routines: a) company credit control reports; b) updating the credit analysis system database; c) in the event of a succession, the "successor" loses its credit limit and the "successor" will be assessed by the credit analysis system for compliance; d) in the event of a change of operator/controller, it will be assessed by the credit analysis system for compliance; e) disapproval of credit for companies undergoing judicial reorganization or with a high degree of indebtedness, except with the approval of the company's management; f) requiring advance payment of purchases for customers with a previously canceled credit limit; g) canceling the credit limit for customers who have not made any purchases for more than 120 days; h) reviewing the credit limit for customers who make purchases for less than the credit limit.

Step 4 - Review the Credit Limit:

Responsible: Credit Coordination.
Tools: system connected to the *credit score* (Serasa).

Criteria: a) high-risk clients will be analyzed through the credit manual, and if they make any changes to their registration, they will be submitted to the approval flow again; if they are not at imminent risk, the credit will be renewed; b) clients with a favorable track record in terms of fulfilling their debts may have their credit limit increased, if the parties are interested; c) the credit limit will be automatically adjusted when there are contractual premises determining such an adjustment, or even when there is a monetary adjustment for any of the components that form the client's price. This will be done with the approval of the company's management, which will stipulate the maximum amount of the adjustment and the date on which it will come into effect; d) there can be no exclusion of a client belonging to a company if there are outstanding debts in one or more companies belonging to the company; e) in order to reallocate limits between companies in the same company, the transferring client cannot have a remaining limit lower than its current account; f) use the risk classification, as shown in Table 3 below:

Table 3
Frequency of credit review

Risk	Frequency
Bass	Annual
Average	Half-yearly
Warning	Half-yearly
High	Quarterly
Highest	Monthly

Source: *Research data.*

Step 5 - Guarantees:

According to Santos and Famá (2007), the following guarantees are commonly negotiated within a credit concession: a) Letter of Guarantee: This is a contract in which the guarantor guarantees compliance with the debtor's obligations. If the debtor fails to meet his obligations, the guarantor is responsible for paying compensation or a fine. It can be a Personal Letter of Guarantee (Individual or Legal Entity), signed by an individual and legal entity, with sufficient assets to cover the debt, or a Bank Letter of Guarantee, signed by a banking institution, the amount of cover for which is determined by the assigning institution; b) Mortgage: this is when real estate is put up as a guarantee for the fulfillment of contractual obligations, where it remains at the creditor's disposal until the debt is settled. It needs to be registered with a notary via sale. In the event of default, the right of ownership and possession of the asset is transferred to the creditor; c) Surety bond: This is the use of a specific pledge of credit securities, which can be bills of exchange, credit lines, shares, among others. It only occurs when the securities are available to the creditor through a public registry. If the securities involved in the pledge are public debt securities, they need to be registered with the relevant tax agency; d) Fiduciary Alienation: This is a transfer of ownership of the asset from the debtor to the creditor, where the debtor remains in direct possession of the asset in question, as a trustee, until all contractual obligations are fulfilled.

Step 6 - Relevant documentation:

For a complete credit assessment, the following documentation must be presented, which will provide the registration information needed for the research company to obtain the client's profile from the *credit score*. These are a) CNPJ card (internet); b) Copy of the ID and CPF of the company's owners/partners; c) Copy of the Articles of Association and amendments; d) FGTS Negative Certificate (internet); e) Copy of the INSS Negative Debt Certificate; f) Copy of the Municipal Negative Debt Certificate; g) Copy of the State Negative Debt Certificate; h) Copy of the Labor Debt Clearance Certificate (CNDT); i) Copy of the Civil Debt Clearance Certificate; j) Commercial references (minimum of 3); k) The company's main clients and the average value of the products or services sold; l) Turnover over the last 12 months; m) Balance Sheet; n) Profit and Loss Account for the year.

4 Results and Analysis

Using the credit granting guidelines proposed in the previous section, together with the inherent theoretical references, which led to the proposition of the steps for a company's credit coordinator, credit analyses were carried out on two of the company's clients.

In the credit analysis of the company "*alfa*", according to the information provided, it requested maintenance services for its management systems. According to the history known through the routine contracting relationship, company "*alfa*" has delayed payments at specific times, in which the overdue amount was paid a few days late. However, this information must provide a realistic picture of the company's profile.

So, to verify the credit analysis's applicability, the company "*alfa*" was asked for the documentation indicated in the steps above so that the information could also be used to consult the *credit score*. In this consultation, the following information was collected: a) CNPJ with no restrictions; b) date of foundation in Sept/1992; c) has been contracting services with XYZ since Mar/2004; d) share capital not informed; e) affiliated with other companies that are not XYZ clients; f) has outstanding loans with financial institutions; g) average probability of default of 5% for six months.

Given the data described above, a preliminary assessment of the client is that he is a good payer and is classified as a low-risk client.

However, the steps show that the "*alpha*" client's information in the service contract documents filed in the last 12 months revealed: a) they contracted a total value of services from XYZ of R$ 36,800.00; b) the R$ 36,800.00 was paid 94% on time, 2% between 1 and 5 days and 4% over five days; c) they have R$ 8.365.00 due, with no debts overdue; d) the customer requested 45 days to pay the balance due; e) the customer has never offered any payment guarantee in his contracts; f) the customer has no time-barred debts with XYZ.

On the other hand, similarly to what was done with the "*alpha*" client, the "*beta"* client was analyzed. Thus, a single query was made to the *credit score* for the information collected, where the following information was obtained: a) CNPJ with restriction recently removed; b) Date of foundation in Jul/2005; c) has contracted the services of XYZ since Sep/2011; d) share capital of R$ 185,000.00; e) is not affiliated with other companies; f) six occurrences in REFIN (unpaid debt service), totaling R$ 7. 296.00, with the most recent debt of Aug/2021; g) two other occurrences in REFIN (unpaid debt service), totaling R$ 7. 296.00, with the most recent debt of Aug/2021.296.57, with the most recent debt dating back to Aug/2021; g) another two occurrences in REFIN, totaling R$ 18,458.31, between Apr/2019 and Aug/2020; h) two protests totaling R$ 7,564.47 in Dec/2017; i) three bad checks issued between Jul/2018 and Dec/2019; j) one lawsuit occurring in Oct/2016; k) average probability of default of 100% for six months.

Given the data described above, a preliminary assessment of the "*beta*" client is that it is classified as being at imminent risk and classified as a client with a high potential for default.

Following the analysis of the steps, the "*beta*" client's information was collected from the service contract documents on file. In the documents consulted, the company's information for the last 12 months was collected: a) the client has not contracted XYZ services in the last four months; b) they contracted an amount of XYZ services of R$ 18,960.00 in the first half of 2021; c) the R$ 18,960.00 was paid 76% on time, 14% between 1 and 5 days and 10% over five days; d) they have R$ 676.49 due, R$ 1.803.28 overdue in the period 11-90 days and R$ 751.18 overdue for more than 90 days; e) the client asked to renegotiate the outstanding balance in 3 installments, the first of which is due in 30 days, where he also asked for fines and interest to be disregarded, the application of which is the subject of a previously signed contract; f) the client has never offered any payment guarantee in his contracts; g) the client has no time-barred debts with XYZ.

It can be seen that credit approval is more likely for the "*alpha*" customer, while rejection is more likely for the "beta" customer.

Using all the information gathered, we can see that customer "*alpha*" has a profile that makes him suitable for all the payment methods offered by XYZ, with the following considerations:

a) commitment to payments, whose punctuality performance reached 94%;
b) there are no records of the client and affiliates with credit protection agencies;
c) according to the Serasa Rating, presented a low degree of risk;
d) the payment period for the balance due was consolidated at 45 days, as shown above;
e) However, given the analysis of the "*alpha*" profile, it was recommended that there should be no manual release of orders placed by the customer.

As for the "*beta*" customer, he has a profile that makes him unable to automatically practice all forms of credit granting, given the following considerations:

a) irregular payment routine, whose punctuality performance reached 76%;
b) there are recent records of the client with credit protection agencies;
c) according to the Serasa *rating*, showed a very high probability of default;
d) The payment of the debt was negotiated in a single installment, including interest and fines, for a payment deadline of 15 days;
e) However, it was recommended that new sales could only be made via advance payment.

During the COVID-19 pandemic, several credit and liquidity preservation concerns have been propagated above all by the financial system about the increased risk of default. For organizations in general, it was no different. To mitigate these risks, even in non-financial entities that operate with credit concessions in their commercial activities, *credit scoring* was adopted, as it is used in financial institutions to evaluate and classify credibility when granting credit to clients. It was noted, therefore, that such an assessment is feasible and necessary so that organizations can also preserve their financial risks.

However, it was clear that credit assessment must balance rigorous and conservative analysis and ensure that eligible companies have access to financial resources. It was noted that it is necessary to complement the qualitative analysis in greater depth to obtain as much information as possible for decision-making. For example, it is essential to consider the history of defaults and the underlying causes.

Following the analyses for "*alpha*" and "*beta"* clients, this work, which focuses on credit analysis by non-financial legal entities during the COVID-19 pandemic, offers significant theoretical contributions to validating criteria when granting financing. The importance of considering relevant risk factors (ratings) to influence financing decisions is highlighted, providing a robust theoretical foundation for the practical analyses conducted within the scope of this study.

The analysis aims to find ways of minimizing default in their negotiations with customers who take out loans. In this respect, this study corroborates the findings of Dahooie *et al.* (2021), reaffirming the importance of establishing forms of *credit scoring to* assess the credibility of customers in terms of their ability to pay.

The existence of numerous methodologies in risk analysis has been supported by Santos (2008) as being able to occur without a specific standard being used but instead adapted as long as there is a quantitative analysis of the data collected from the client and complemented by another qualitative analysis with more detailed information. In this way, credit analysts can gain an in-depth insight into the nature and extent of the observable analytical discrepancies.

In the case in question, when observing that the risk assessment considers factors such as history, documents, guarantees, default, cash flow, indebtedness, governance and market, these make up an analysis that covers economic-financial and behavioral aspects, capable of generating classifications and credit scores between the client and the legal company under analysis. However, in the COVID-19 pandemic, a risk scenario must be considered to complement the conditions observed in the relationship and behavior, as evidenced by the history between the client and the company. This analytical expansion validates the theoretical aspects pointed out by the 5 Cs, according to Carvalho *et al.* (2014), Neoway (2021), and Santos (2003).

In this way, the contributions align with the literature that discusses credit risk, risk assessment methods when granting credit and the importance of validating the credit practices applied when granting financing.

If, on the one hand, risk assessment takes place through classification, in which a risk *rating* is assigned to the customers analyzed, ranging from AAA to D, this classification serves to improve the company's financial decisions, minimizing the risk of default and guaranteeing the financial security of its commercial operations. However, the breakdown occurs with the need to complement the analysis more in-depth qualitatively, seeking to obtain as much information as possible for decision-making. In this context, the 5 Cs form the basis for a more predictive risk analysis. This means, for example, considering the history of defaults and the underlying causes.

5 Final considerations

When we consider the financial transactions commonly carried out between companies, the success of credit analysis is directly and sensitively linked to the information collected. This information must necessarily contain accurate and confirmed data. Based on this dynamic, credit analysis is applied to companies that offer payment options to their customers, which also represents a way of complementing and determining their risk ratings. This type of analysis aims to check the customer's history (especially the most significant in terms of demands for credit) about the company and even its performance in the market so that the possibility or otherwise of granting credit can be assessed. In an experimental observation at service provider XYZ, it was possible to assess how to classify the risks offered by a particular client when contracting services to minimize default within the company and guarantee the receipt of amounts related to its financial obligations.

The assessment of risk in the granting of credit by a company that is a legal entity to another company that is also a legal entity (clients) during the commercialization of services whose credit is inherent to the operation made it possible to observe as a methodological premise the guidelines for granting credit, which have commonly been used in financial institutions, and which have now been adapted for the XYZ entity. In other words, this study made it possible to assess the risks presented by its clients about contracting services, minimize default, and guarantee receipt of the amounts owed.

This finding precedes, above all, the studies by Carvalho *et al.* (2014), Kalimipalli and Nayak (2022) and Neoway (2021), seeking pragmatism in which it was noted that, as much as there is a demand and availability of resources in the form of financing the customer in the acquisition of a particular good or service, with the commitment of future settlement, the establishment of a *credit score* is essential. Financial institutions, for example, adopt the *credit score,* often adapting it to qualitative analysis with the 5 "Cs" of credit: character, capacity, capital, collateral and conditions for assessing the viability of granting, which cooperate to establish a risk rating.

From the point of view of conjectural analysis between lender and borrower, maintaining this same holistic view of the borrower's actual economic situation through the lens of a company in its commercial relations with other companies, even if both are micro-entrepreneurs, it was revealed that the *credit score* evaluation is also a way of observing the likelihood of a company paying its debts according to the established terms, whether through payment history, amount of debts, length of credit, types of credit used and recent credit inquiries, as examples.

This study of legal entities with ongoing commercial relationships for goods or services also observed that this classification can be extended to a *rating score.* In other words, the company providing the credit as a way of financing its client for the acquisition of a good or service can establish a risk rating, assigning mechanisms to assess its ability to meet its financial obligations so that scores are established, whose automatic approvals are categorized according to the risk classes of the client companies.

Given the problematization presented, it was possible to verify that company XYZ has adopted a set of methodological steps involving applying credit analyses and using the *credit score* to evaluate its "*alpha*" and "*beta"* customers. This approach provided a detailed view of each customer's risk profile.

In the case of the "*alpha*" customer, who was initially considered low risk based on the *credit score,* further qualitative analysis revealed additional information, including payment history and financial behavior. Although the customer had shown good punctuality in previous payments, recent documents showed a less favorable financial situation, suggesting the need for caution in credit-granting decisions.

On the other hand, according to the credit score, the "*beta*" customer was classified as having a high potential for default. The complementary qualitative analysis confirmed these concerns, highlighting the irregular payment history, occurrences in the service of unpaid debts, protests, bad checks and a significant probability of default.

The results cooperated with the answer to the initial question, indicating that company XYZ, when implementing risk assessment practices, seeks to harmonize a careful analysis with the guarantee of access to financial resources and that external eventualities, such as the COVID-19 pandemic, reveal that credit assessment should contemplate not only quantitative data but also the underlying causes, validating the theoretical aspects in stages, which allows capturing perceptions about the 5 Cs.

Therefore, if there are automatic *credit* assignment mechanisms in financial institutions, in which the *credit score* and *rating score* are tools that guide this dynamic, these can also be applied, with the necessary adaptations, as observed in company XYZ. This practice would help predict whether or not credit is approved for financing, making marketing by company XYZ more flexible and dynamic without impacting the increase in defaults.

As suggestions for future studies, approaches that could be explored were found, such as: i) analyzing the implementation and effectiveness of the *credit score* and *rating score* metrics in companies of various sectors and sizes, as well as comparing different risk analysis methodologies and their impacts on financial decisions; ii) investigating the reflections of the flexibility and dynamics that such classifications have made possible for businesses; iii) evaluating their effectiveness on occasions of eventualities that have occurred, such as the COVID-19 pandemic; iv) identifying the feasibility or possibilities in adopting advanced technologies, such as the use of artificial intelligence as a way of speeding up credit analysis with risk classification.

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