The Role of Artificial Intelligence, Financial and Non-Financial Data in Credit Risk Prediction: Literature Review

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Abstract. Small and medium-sized enterprises (SMEs) are of major importance in world economies and job creation. Financing is one of the key issues for SME development since SMEs are often considered riskier than large companies. It is argued in the literature that artificial intelligence (AI) and non-financial data could increase the financial inclusion of disadvantaged groups, such as SMEs. This article presents an overview of selected studies on credit risk prediction from the 1960s to 2022, covering topics of research work applying classical statistical methods, studies using AI methods on traditional financial data and studies applying AI methods on non-financial data. Literature overview results showed that the inclusion of non-financial data in credit risk prediction models could increase credit risk prediction performance, while AI methods can enable the inclusion of non-financial data. Since non-financial data potentially could be used as alternative data in credit prediction models, AI and non-financial data could help to increase access to finance for SMEs.
Keywords: *credit risk, small and medium-sized enterprises, artificial intelligence, non-financial data.*

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Introduction

Relevance of the article

It is argued in the literature, that artificial intelligence (AI) and non-financial data could increase the financial inclusion of disadvantaged groups (Aitken, 2017; Mhlanga, 2021). This is particularly relevant in the case of small and medium-sized enterprises (SMEs), which are of major importance in world economies and job creation. Financing is one of the key issues for SME development. SMEs are often considered to be riskier than large companies and one of the main reasons for that lies in the quality and availability of financial data. The lack of data creates an information asymmetry between banks and SMEs which seek bank financing, resulting in higher demands from banks to hedge against potential risks (Pettit, & Singer, 1985; Yoshino, & Taghizadeh-Hesary, 2018; Mhlanga, 2021). Consequently, companies sometimes fall into a vicious circle when they cannot access bank financing because banks do not have sufficient financial data about SMEs, and the company cannot afford higher borrowing costs (Aitken, 2017; Rybakovas, & Žigienė, 2021).

Level of problem investigation

Non-financial data potentially could be used as alternative data in credit risk prediction models, which could help to increase access to finance for previously excluded entities. From an economic perspective, this could not only improve the financial inclusion of frequently credit-invisible SMEs but also stimulate economic growth in related areas (Sadok et al., 2022). Some FinTechs are already applying AI and non-financial data to evaluate the creditworthiness of clients and make decisions on whether to extend the credit, what should be the terms of funding or what actions should be taken in managing the risk of the loan portfolio (Sadok et al., 2022). However, the use of such unconventional data among traditional banks is rare.

Scientific problem

Can AI and non-financial data increase the financial inclusion of disadvantaged groups such as SMEs?

Object of the article is the impact of AI methods and non-financial data on the financial inclusion of SMEs.

Aim of the article – to overview and compare credit risk prediction methods using financial and non-financial data, which are presented in scientific literature.

Objectives of the article:

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1. To perform a literature analysis of the application of classical statistical methods in credit risk prediction.
2. To conduct a literature analysis of the application of AI methods on traditional financial data in credit risk prediction.
3. To overview the literature on credit risk prediction using AI and non-financial data.

***Methods of the article*:** literature review.

1. Theoretical analysis of traditional and unconventional methods and data in credit risk prediction

Definitions. Credit risk could be defined as "the potential that a bank borrower or counterparty will fail to meet its obligations in accordance with agreed terms" (Principles for the Management of Credit Risk, 2000, p. 1). One of the key elements of credit risk is the probability that the borrower will default on his or her obligations (Brown, & Moles, 2014). Although the credit risk prediction topic has been widely discussed in scientific literature since the 1960s, there is no clear consensus on the default definition. Many studies focus on bankruptcy prediction (Altman, 1968; Ohlson, 1980; Odom, & Sharda, 1990; Zhang et al., 1999; Charalambous et al., 2000; Shin et al., 2005; Hewa Wellalage, & Locke, 2012; Tobback et al., 2017), which is considered as an extreme case of default when the entity is declared bankrupt by a court and is dissolved (Brown, & Moles, 2014). Others use terms such as failure or failing company (Beaver, 1966; Tam, & Kiang, 1992; Bell, 1997; Horta, & Camanho, 2013; Lextrait, 2022), referring to the inability to fulfil financial obligations, which do not necessarily end up as bankruptcy.

1.1. Overview of the application of classical statistical methods in credit risk prediction

One of the first studies in the field of credit risk prediction was conducted by Beaver (1966), where he performed a univariate analysis of six financial ratios. The analysis was very limited as it assessed only one financial ratio at a time. A couple of years later, Altman used the Multiple Discriminant Analysis (MDA) method to predict the default of the companies (Altman, 1968). MDA soon gained popularity in credit risk prediction studies. However, it had several drawbacks and required satisfying assumptions, which with real financial data were difficult to satisfy. Therefore, other methods were suggested in later studies, including but not limited to multivariate regression analysis (Orgler, 1970), Naïve Bayes classifier (Sarkar, & Sriram, 2001; Dastile et al., 2020) and logistic regression, which is one of the most popular methods for scoring borrowers until these days both in the academic world (for example, used by (Wiginton, 1980), (Sun, & Li, 2009), (Dong et al., 2010), (Hewa Wellalage, & Locke, 2012), (Thiel, & Raaij, 2019) and (Yin et al., 2020)) and in the banking industry (Dong et al., 2010) as it does not require satisfying as many assumptions as other statistical methods (Ohlson, 1980; Hewa Wellalage, & Locke, 2012) and is appreciated due to its simplicity and interpretability (Dong et al., 2010; Óskarsdóttir et al., 2019; Dastile et al., 2020). Nevertheless, logistic regression requires fulfilling certain assumptions, such as a sample should be random and large, there should be no collinearity between explanatory variables and observations should be independent (Ptak-Chmielewska, 2019).

Overall, the limitations of classical statistical methods lie in the strict assumptions that must be met to rely on the results and established functional forms between dependent and independent variables, which makes the real-world application of these methods difficult (Kim & Sohn, 2010). These limitations stimulated research of other credit risk prediction methods, including but not limited to AI methods.

1.2. Literature overview on credit risk prediction using AI and traditional financial data

Traditional financial data mainly include various financial ratios calculated using data from financial statements, which measure liquidity, profitability, turnover, solvency and similar areas. Many various AI and other intelligent methods are found in the credit risk prediction literature, such as neural networks, support vector machines (SVM), decision trees, k-nearest neighbours algorithm and various modifications of these methods as well as ensemble methods, such as random forests or Gradient Boosting Decision Trees models. It should be noted that this list is not finite and includes more frequently mentioned methods in the reviewed literature.

In the case of traditional financial data, neural networks and SVM were one of the most frequently mentioned methods in overviewed literature. Studies comparing neural networks with other methods, such as MDA, linear discriminant model, logistic regression, k nearest neighbours method and decision trees showed that the neural networks can achieve equally well or higher accuracy (Odom & Sharda, 1990; Tam & Kiang, 1992; Bell, 1997; Zhang et al., 1999; Charalambous et al., 2000). SVM is also presented as a promising method in credit risk prediction, capable to outperform other classical and AI methods, such as neural networks, especially when the dataset is smaller (Shin et al., 2005; Lahmiri, 2016).

Generally, one of the benefits of AI is that it does not require as much data processing and satisfying assumptions as traditional statistical methods and allows faster processing of potential borrowers' applications without compromising the quality of processing (Sadok et al., 2022). On the other side, most AI models are criticised for their lack of opacity and interpretability (Dastile et al., 2020; Sadok et al., 2022). However, the most recent studies are addressing the issue of AI model opacity by applying post-prediction explanation models such as Shapley additive explanation (SHAP) (Lextrait, 2022). Although most of the overviewed articles claim that AI methods can achieve equally well or better performance compared with traditional statistical methods, other studies claim that the performance results of AI models are debatable, especially when only traditional financial data is used. For example, Sadok et al. overviewed studies on the topic of credit analysis using AI and concluded that AI offers only minor performance improvements when applied to the same data set as classical statistical methods (Sadok et al., 2022). However, AI methods allowed the inclusion of new types and larger volumes of data, often referred to as big data, which seems to be able to improve credit risk prediction performance (Sadok et al., 2022).

The possibility to include non-financial data in credit risk prediction could expand opportunities to receive financing for SMEs, which usually are lacking quality data for credit risk assessment. Although the application of classical statistical methods and AI on traditional financial data in credit risk prediction has been widely analysed for the past several decades, the application of non-financial data in credit risk prediction is less explored. Thus, the next section will overview empirical studies, which used AI and different types of non-financial data in credit risk prediction.

1.3. Literature overview on credit risk prediction using AI and non-financial data

Simple non-financial data. Non-financial data could include noncomplex information about the company's main activity or sector, the company's size, location, age, whether the company has employees and the number of employees (Horta, & Camanho, 2013; Lextrait, 2022). Such simple non-financial data do not necessarily require sophisticated AI models and could be analysed using both AI and classical statistical methods. Horta, & Camanho (2013) found that the credit risk prediction model achieved better results when it included not only financial but also non-financial variables. Another financial, but unconventional variable found to improve credit risk prediction performance is payment behaviour data. For instance, Malakauskas, & Lakstutiene (2021) found that the best results were achieved when the dataset included information about overdue payments, while Ciampi et al. (2020) found that including payment behaviour data in a model with traditional financial ratios could improve prediction performance, especially when the size of the company gets smaller. Other studies investigating credit risk prediction have included industry-specific non-financial variables, such as technology evaluation factors (Kim & Sohn, 2010) or subjective criteria such as the morality of the SME, partnerships and state of production capacity among others (Gulsoy, & Kulluk, 2019).

More complex non-financial data. Alternatively, recent studies started to use more complex data in credit rating models, which require more sophisticated methods of analysis. The data could be of a sizeable amount and include unstructured information, language, perceptions and visual information, inter alia (Sadok et al., 2022). For example, Óskarsdóttir et al. (2019) used call detail records provided by the telecommunications operator and commercial bank data about customers to create call networks and forecast the creditworthiness of consumers applying for a credit card. Researchers found that models incorporating calling behaviour features performed better compared to models containing only conventional data and call logs data could even be used as the only data source for evaluating consumer credit risk. Tsai, & Wang (2017) used textual information from financial reports and sentiment analysis with finance-specific words to evaluate the riskiness of publicly traded companies. The results of the analysis confirmed that textual information from financial reports, especially financial sentiment words, is important in credit risk prediction. Social media information is another example of data used for credit risk prediction. Yao et al. (2022) tested if financial social media data can improve credit risk prediction performance in the supply chain of listed companies in China. The authors applied sentiment analysis to analyse the data. Results confirmed the hypothesis that social media data improves credit risk prediction model performance and even in most cases social media-based features, especially time-weighted text sentiment feature, have better prediction power than traditional data-based features because it has forward-looking information about enterprise credit risk. Yin et al. (2020) used publicly available legal judgment data on China's SMEs' for credit risk prediction, where they constructed variables from legal judgements information, which indicated how many judgements the company has in distinguished legal judgement categories. Authors found that adding certain features extracted from legal judgments to a model with conventional variables improves model performance. Tobback et al. (2017) used information about current and past management and directors of Belgian SMEs and their links with other companies to predict credit risk. Authors hypothesised that a company, related to many other bankrupt companies, have a greater failure rate, particularly when this company is in a bad financial position. The authors found that relational data on its own does not have enough predictive power but supplementing a financial data-based model with relational data improves prediction performance, especially when predicting the bankruptcy of the riskiest SMEs.

Overall, in most of these examples, it was concluded that non-financial data shows promising results in credit risk prediction and some authors even stated that non-financial data could be used as the only data source for evaluating credit risk (Óskarsdóttir et al., 2019). However, non-financial data has some drawbacks. For instance, sometimes predictive power of non-financial data can overshadow traditional data-based features. Therefore, some authors emphasised, that it is important to use non-financial data only as supplementary data showing good financial behaviour for subjects lacking traditional information for credit assessment (Óskarsdóttir et al., 2019). In addition, some forms of non-financial data are already questioned in the literature. For example, Wei et al. (2016) stated that although initially consumer credit scoring models based on social media data might improve the accuracy of credit scores and improve the financial inclusion of disadvantaged groups, later consumers might start to deliberately alter their social networks to improve their credit scores.

Overview of applied AI methods. Neural networks and SVM mentioned previously were also popular in studies using non-financial data. Besides these methods, there were also used neural networks-based Kohonen maps, Gradient Boosting Decision Trees (GBDT) models, extreme random tree, random forests and decision tree-based algorithms. The latter two methods – decision trees and random forests, were mentioned by several authors as best-performing models (Gulsoy, & Kulluk, 2019; Óskarsdóttir et al., 2019; Malakauskas, & Lakštutienė, 2021; Yao et al., 2022). Another observation which could be drawn from the reviewed literature is that a variety of different applied AI methods in overviewed studies implies that when predicting credit risk with AI, there is no one-size-fits-all and the most suitable methods might differ depending on data. Furthermore, credit risk prediction results can be assessed by various measures, such as accuracy, specificity, sensitivity, etc. and some authors noticed, that different methods provide the best results under different measures, thus it is important to use multiple AI methods when predicting the credit risk (Lahmiri, 2016).

Conclusions

1. Although some statistical methods are still widely used both by banks and in the academic world, they have several drawbacks which make it challenging to apply these methods in real-world situations. The main downsides of classical statistical methods listed in the literature include the predetermined functional relationships between dependent and independent variables and the rigid assumptions that must be followed to rely on the results.
2. AI methods are promising alternatives to statistical methods, as they do not require as much data processing and satisfying assumptions and can be applied to analyse non-financial data. However, it is important to try multiple AI methods as the best-performing AI methods vary depending on the data.
3. Various types of non-financial data have already been tested and demonstrated promising results in credit risk prediction modelling. Examples of simple non-financial information include company size, location, industry, ownership-related variables and payment behaviour data. While more complex non-financial data examples include mobile phone call information, connections of directors and managers of the company to other entities, public legal judgments information, social media information and textual information from financial statements.
4. Overall, an overview of empirical literature showed that the inclusion of non-financial data in credit risk prediction models can increase the prediction performance of the models compared to traditional models that use only financial data. Since non-financial data potentially could be used as alternative data in credit risk prediction models, it can be concluded that AI and non-financial data could help to increase access to finance for SMEs.
5. The main limitation of this study is related to the literature search and selection process for the literature review, which included authors' judgemental decisions, therefore, conclusions of the review might be biased and the present paper should be considered as a starting point for future research on the topic.

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