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Abstract

During the last decade, the increase in computational capacity, the consolidation of new data processing methodologies and the availability of access to new information concerning both individuals and organizations, aided by the widespread internet usage, has increased the development and implementation of artificial intelligence (AI) within companies. The application of AI techniques in the banking sector attracts wide interest as the extraction of information from data is inherent to banks. As matter of fact, for many years now models play a crucial role in several banks processes and are strictly regulated when they drive capital measurement processes. Among banks' risk models a special role is played by credit ones, as they manage the most relevant risk banks face and are often used in regulatory relevant processes. The new AI techniques, coupled with the usage of novel data, mostly unstructured ones related to borrowers' behaviors, allow for an improvement of the accuracy of credit risk models, that so far relied on structured internal and external data.

This paper takes inspiration from the Position Paper Aifirm 33/2022 and its English published translation (Locatelli, Pepe, Salis (eds), 2022.

The paper is focused on literature review regarding the most common AI models in use in credit risk management, also adding a regulatory perspective due to the specific regime banking models are subject when they are used for regulatory purposes.

Furthermore, the exploration of forthcoming challenges and future advancements considers a managerial perspective. It aims to uncover how credit risk managers can leverage the new AI toolbox and novel data to enhance the credit risk models' predictive power, without overlooking the intrinsic problems associated with the interpretability of the results.

Keywords: credit risk models, artificial intelligence, bank management, unconventional data

JEL Code: C00, C40, G21, G32, O30.

1. Introduction

The growing availability of increasingly digitalized data flows is changing the way companies can stand to gain a real competitive edge by harnessing these data and employing sophisticated processing techniques to cut costs and implement decision-making processes that are as data driven and automated as possible, also gaining in efficiency.

The banking and financial service industry is, by its very nature, specialized in generating and interpreting information, and is also characterized by managing financial and non-financial risks, by using a large amount of data that contribute to develop specific and advanced models for risks measurement.

The critical role of these models in risk management processes and the regulatory regime banks are subject to, make risk models the object of a strict supervision that inevitably affects banks' choices.

In this regard, banks must avoid being trapped by "traditional models" as the ability to harness developments in artificial intelligence (AI) constitutes a critical success factor in the competition with new market participants – Fintechs – whose proposition is often built around the usage of AI capabilities.

Hence, an effective deployment of AI for their day-to-day activities will play a special role in keeping banks up to the challenge of the market evolution. Lending and pricing decisions making are a first example, as well as monitoring exposures for risk management and measurement, and performance assessment.

Among others, credit risk continues to deserve a special attention and prioritization in banking management, due the critical role banking credit plays in European financial and economic systems, to support growth and investments. The "key" of a virtuous functioning of the system based on a proper credit assessment of the borrower, the process by which the lender evaluates the creditworthiness of the counterpart by quantifying the risk of loss and by evaluating the "cost" of this risk in terms of cost of lending. Since the development of credit scorings and ratings, credit decision-making has expanded to encompass risk-based pricing, the Know Your Customer (KYC) principle, independent evaluation standards, and internal credit scoring. This process involves multiple entities and relies on extensive datasets sourced from external applications, open banking data, and various third-party sources (Zhang et al., 2014).

The paper aims to conduct a literature review focusing on the prevalent AI models utilized in credit risk management within the banking sector. The paper evaluates the feasibility of implementing these models within current banking practices. It offers examples to understand significant challenges associated with integrating unstructured data. Additionally, it offers a focus on the regulatory perspective, emphasizing the significance of validating models when employed for regulatory purposes.

Section 2 is focused on new data, especially unstructured data, that are included in AI techniques. Sections 3 and 4 summarize the most common AI models and some application in credit risk management: nowadays financial institutions can have access to a huge

amount of new data, for example those coming from digital payments, that can help understanding borrowers' behaviours. To do so banks must upgrade their systems and capabilities to make robust credit decisions in a fast-changing context (Zensar Technologies, 2023).
Section 5 discusses forthcoming challenges and future advancements, to understand the ways credit risk managers can leverage the new AI toolbox and new data in order to enhance the predictive capacity of credit risk models. This examination also addresses the inherent challenges tied to interpreting the results.

2. New data in the context of credit risk models

As mentioned, in addition to the information that banks acquire during their business relationship with customers, intermediaries have traditionally been able to acquire additional information externally (i.e., macroeconomic data, credit reports stemming from the Central Bank credit register and information generated by other credit bureaus). The field of "additional" or "alternative" information has substantially expanded in the recent years, due to the progressive digitalization of the economy leading to businesses and individuals generating vast quantities of information most of which is unstructured and have both financial and non-financial source and content (Altman et al. (2010) for the relevance of soft and non-financial information in credit evaluation of microfirms).
We have several examples of such data. They include online information, news and stories, newspaper articles, and social media posts and comments, which can contribute to define individual's or company's "online reputation". Moreover, other data describe consumer habits and preferences, such as their daily financial transactions: the increasing penetration of debit and credit cards and electronic payments generates a large and new set of information not available up to now.
A major regulatory development, the second European Payment Services Directive (PSD2), then made this information more accessible and thus easier to be used for credit scoring purposes. The new Directive has made information arising from financial transactions much easier to use as, on one hand, it has required financial intermediaries to give third parties access to information that was, until then, exclusively the prerogative of such intermediaries while, on the other, it has made it possible for the same banks to use third-party information when the potential new customers allow to do so. Other data refer to digital footprints, geolocation, utility payments, and the usage of TLC services (Zensar Technologies, 2023).
The whole amount of these alternative data can make credit risk management and borrower's evaluation more effective. The larger the datasets in use, the more complete analysis supporting the credit score: a larger number of diverse data sources is becoming more and more now accessible to financial institutions with the purpose to make credit and financial evaluations and decisions more effective, and ultimately fairer.
Berg et al. (2018) demonstrated that digital footprint variables like email domain and type of device have a better chance than the traditional credit bureau scores at predicting the default of a borrower or late payments in loans' installments and also they argue that a lender that refers to both traditional credit scores and digital footprint of the borrower in its models will be able to make a better credit decision: credit access can increase without compromising the loan quality. The variables used to investigate the digital footprint of the applicants are usually the email domain, the type of device used for the connection, the time at which the contact happened. Taken together, these variables can be useful to investigate certain features of the credit applicants that otherwise would have not been examined (e.g. the type of device is easily associated with applicant's level of income).
In 2022 a study performed by Forrester Consulting on behalf of Experian (Experian, 2022) has highlighted the need to focus on leveraging alternative data and emerging technologies to improve the credit decisioning processes of an organization. More in detail, the surveyed lenders consider that data augmentation remains a top priority for credit risk assessment: 77% of lenders consider that the high or critical priority to leveraging open banking to access real-time data, while the percentage is about 75% both for leveraging new data sources (alternative data) and emerging technologies (AI).
In this context of greater availability of "alternative" data, the Covid-19 pandemic, increased the overall uncertainty regarding the macroeconomic conditions, reinforcing the need for banks expand their traditional datasets to include information updated in real time, or gathered from less consolidated sources. Such measures have been necessary to compensate for the loss of sensitivity suffered by "traditional" rating instruments during the pandemic. This extreme event impacted the "traditional" information used in credit rating systems (EBA, 2020a), as loan moratoria makes it more difficult to assess the evolution of a borrower's financial position and thus its ability to repay, crippling the rating systems' aptitude to correctly gauge the customers' riskiness, risk that could materialize once the various relief measured were lifted. This context therefore reinforced the need for intermediaries to expand their datasets and deepen their analyses of the data they already had, in order to identify, far enough in advance, any "zombie" borrowers, i.e. obligors surviving solely thanks to the relief measures and for which the banks needed to determine the most appropriate steps to take in order to mitigate credit risks[1].
In light of the above, the modelling of the counterparties' creditworthiness can therefore take advantage of the usage of alternative data in multiple manners.
The banks use financial transactional data to integrate and refresh company's financial statement. This approach prevents reliance solely on outdated financial information, which tends to lose its relevance swiftly during periods of regime change.

[1] Moreover, the priorities of the ECB Banking Supervision of 2021 include: "[…] banks' capacity to identify any deterioration in asset quality at an early stage and make timely and adequate provisions accordingly, but also on their capacity to continue taking the necessary actions to appropriately manage loan arrears and non-performing loans.", as reported at www.bankingsupervision.europa.eu.

Moreover, by combining bank performance data (i.e., internal, and external performance data) with information released by credit bureaus and "new information" has made it possible to raise the degree of the models' precision, thereby improving their contribution to pinpointing opportunities for development, as well as in the measurement of risks.
The availability of "high frequency" data, accessible in real time or nearly so, enables the construction of models that exhibit greater sensitivity than traditional ones to changes in borrower characteristics. This attribute makes them more forward-looking in nature.
Moreover, incorporation of alternative data can enrich the credit risk models: banks and financial institutions can increase the quality of the loans portfolio, in terms of lower probabilities of default, a higher efficiency in credit decisions leading to a reduction of non-performing loans and default rates. Recent research suggests that AI models can enhance the performance from 10% to 15%, leading to a significative decrease in credit losses from 40% to 20%. Additionally, these models can potentially contribute to a reduction of about 25% in the exposure towards risky customers (McKinsey, 2021b). Furthermore, advanced models can drive revenue growth by enhancing the customer experience (cross-selling), and even lead to higher operating margins by increasing operational efficiency, by easily automating or reengineering some processes thanks to the adoption of new platforms based on AI/ML tools.
The best practice for the optimal use of one's data in the development of cutting-edge credit risk management models lies in the ability to integrate various type of information available on the counterparties evaluated throughout multiple business processes: "structured" or "traditional data" meet a set of predetermined rules in terms of types; "semi-structured data", which contain semantic tags without having the typical structure associated with relational databased; lastly, "unstructured data" do not have a predefined model and cannot be organized into rows and columns (e.g., images, audio and video recordings, e-mails, spreadsheets).
When implementing AI models for credit risk management purposes, the primary challenge lies in handling unstructured data, since even in today's digital world most information available is unstructured. Different structuring techniques can be employed in the analysis of unstructured data: they mainly refer to text analysis and Natural Language Processing (NLP). These techniques utilize algorithms to extract natural language rules, rendering then the unstructured information comprehensible to computers.
The most important procedures include, but are not limited to, topic modelling, where tags are created for specific topics using key words through, for example, Latent Dirichlet Allocation (LDA) which identifies the key words to extract; part-of-speech-tagging, which entails recognizing the type of entity extracted (e.g., an individual, a company, a place), by means of named-entity recognition; sentiment analysis, employed to identify the sentiment, opinion, or conviction of a statement, from very negative to neutral to very positive.
A specific domain where these techniques are gaining notable relevance is the one of banks' transactional data. Transactional data have been used in a wide variety of applications in banking analytics since many years, but their use in the past has been limited to constructing simple aggregated features of structured information, such as calculating the average spending over recent months or determining the total income for the past year, etc. This approach has clear limitations in fully harnessing the potential value of transactional data. This is particularly relevant in the case of unexpected events, where the classical approach could fail to rapidly capture changes in individuals' behavior. For example, amid the Covid-19 pandemic transactional data were extremely useful to track the crisis, and extract insight over the change in mobility and expenditure across different income classes.
One of the steps needed to grasp the powerful information content of transactional data is the categorization, which involves the usage of Natural Language Processing tools allocating transactions to a commonsense "categories" based on the words found in the text elements. For example, once all transactions are gathered in a single repository, after a possible data integration step, those mentioning car-related expenses would be all allocated under the "car" category. To this aim the NPL algorithm will look for different words or acronyms referencing the concept of a car (in Italian "macchina", "autovettura", "assicurazione auto", "meccanico", etc).
A crucial step in the treatment of unstructured data consists in the cleansing of the latter. The main activities in the preparation and cleansing of a text include: the removal of special characters; the standardization of text; removal of "stop words" (e.g., articles, conjunctions, prepositions, commonly used verbs); removal of non-significant words or numbers; and stemming or lemmatization, which reduce an inflected word to its root form (e.g., "go", "went", and "going" would be mapped towards their stem "go").
As the amount of available data increases and the data become more complex, we must keep in mind that the relationship among the different explanatory variables and the target one is not linear. Hence, to effectively capture such increased complexity, the utilization of machine learning (ML) techniques becomes critical.

3. New models for credit risk management

Sometimes there is a sort of "overlap" between Machine Learning (ML) and Artificial Intelligence" (AI). While they are interconnected, AI encompasses a broader scope that involves the creation of IT systems aimed at executing tasks without human intervention. ML, on the other hand, is a subset of AI, that involves specific techniques allowing systems to learn and improve from data without being explicitly programmed.
AI encompasses various methods beyond ML, including expert systems, natural language processing, computer vision, and robotics, among others. These techniques enable AI systems to mimic cognitive functions, learn from experiences, and adapt to new information, extending beyond the specific algorithms used in ML.
Literature analyzed several techniques and tools. An excellent and complete analysis is provided by Breeden (2020), who focused on ML methods as the result of a combination of data structure, architecture, estimator, selection, or ensemble process. More in detail, among these key components, "architecture" represents the step in which the difference between traditional statistical methods (regression approaches, state transition models) and ML (convolutional networks, feed-forward networks, and recurrent neural

networks) comes to evidence. Moreover, according to Breeden (2020), ensemble modelling seems to have a relevant added value in credit risk, because of the typically limited datasets available, as it can combine the forecasts from different model types as they can capture different aspects of the data and they contribute to increase the effectiveness of the model. Ensemble models can be divided into homogenous methods, that combine multiple models of the same type, and heterogenous models where the "mix" aggregates any type of models. Among the first ones, bootstrapping aggregation (bagging), decision trees and random forests are probably the most well-known techniques, as well as boosting, i.e., a process of building subsequent models on the residuals of previous models (Breeden, 2020; Schapire, 2003). Nalić et al. (2020) analyzed the importance of hybridization and ensemble models, increasing the performance of ML algorithms.
Figure 1 contains a graphic representation of the different ways in which the two techniques work. Boosting considers the sequential estimation of the multiple decision trees, whereas Bagging, also known as Random Forests, accounts for multiple decision trees in a parallel fashion. It is worth mentioning that both ensemble techniques can be generalized for different underlying models.

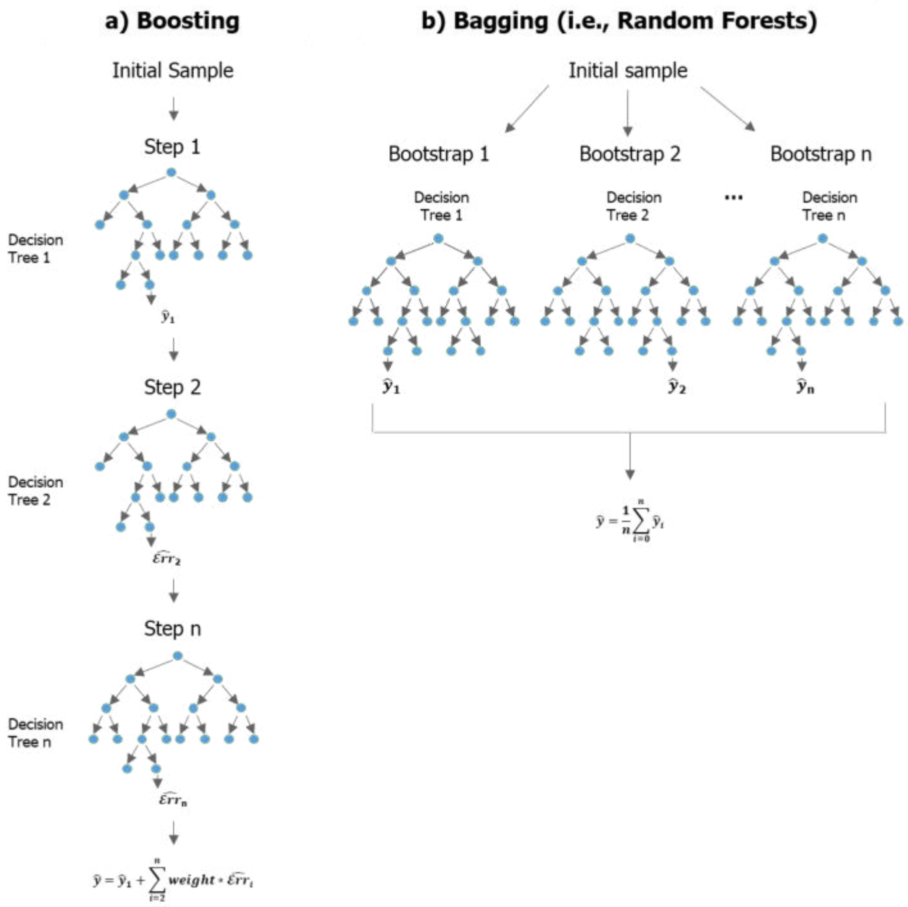

Figure 1: Two different model ensemble techniques. Boosting and Bagging

According to Breeden (2020), several applications of ML to credit risk are in use, following different specific purposes and employing specific explanatory variables. Notably, in credit scoring, decision trees, neural networks, and nearest neighbors worth a mention. More in detail, decision trees are based on an algorithm, whose logic can be interpreted and translated into "if-then" scenario, that follows the structure of a tree comprised of a series of nodes and branches. The nodes represent a macro-class of input variables, in which each node corresponds to a specific linear test function, which establishes the appropriate partitions of the input variables. The branches or, to be more precise, the arches, represent all the properties, or the splitting rules, which determine the path within the tree and, finally, the classifications. These properties/rules are defined in relation to the specific values assumed by the attribute identifying the parent node. Decision trees are very efficient when working with categorical variables, where the classification is expressed through explicit conditions, the algorithm itself determines the significant variables, and the presence of outliers does not excessively affect the result (typically the outlier data will be isolated in peripheral nodes).

Additionally, it's worth noting that random forest is a specific method based on decision trees.

This technique involves replicating the tree's estimation numerous times (often exceeding 1,000 iterations), utilizing only a single subset of the available variables in each iteration. This classification is based on a regression and classification algorithm that creates a forest of decision trees constructed out of multiple datasets, extracted through bootstrapping (random sampling that organizes the various nodes and divides them randomly). The more trees there are in the forest, the better the results of the model will be. It is important for there to be a low correlation between the models entered: in this way, each decision tree created takes independent decisions and thus reduces individual errors, constituting a protective barrier between one tree and another. Certain trees may generate distorted results, whereas others will generate correct results, leading the model in the right direction.

The algorithm named "Nearest neighbors" has the purpose to classify each observation by analyzing the "k" individual closest to it. These models learn from past examples (for example past lending experiences) to collect data and info for a "comparable" loan. The most challenging point is about the identification of "effective" comparable as the success of these methods is related to the uniformity of the distribution of the dataset. If data are scarce or extremely sparse, the reference to past experiences may add value in the quality of the analysis, overcoming interpolation or extrapolation.

Neural networks are often considered the last frontier in AI techniques applied to data modelling. These methodologies are often thought of as a "black box" in terms of the association between the input parameters and the output classification. Neural networks are based on a model that puts the explanatory variables in communication with the target variables through various layers of latent variables, referred to as "hidden layers", consisting of combinations of transformed input variables. A neural network is indeed an "adaptive" system capable of modifying its own structure (the nodes and interconnections) based on both external data and internal information that interconnect and move through the neural network during the learning and reasoning phase. Artificial neural networks are non-linear structures of statistical data organized as modelling tools. They receive external signals on a layer of nodes (i.e., the processor) and each of these "entry nodes" is connected to various internal nodes in the network which are typically organized into several levels so that each individual node can process the signals received, transmitting to the next levels the result of its processing (i.e., more sophisticated, detailed information). It is the hidden layers' task to use the features of the dataset to learn new features. In such cases, the network will use the features it has learned in a hidden layer to learn additional new features that are even more significant in the next layer, and so on until they are used for classification, regression, or clustering in the output layer. One of the most important positive elements of neural networks is that they work extremely well for both classification and regression in deterministic problems.

Furthermore, the classifications that they produce are very robust for noisy data and they are also capable of exploiting relationships between features that are difficult to identify using other modelling approaches. A neural network model may be highly accurate, reflecting the treatment of non-linear data (Giudici et al., 2023).

Neural networks are one of the most extensively tested methods for credit scoring, probably because they are flexible as they can be combined with other algorithms to manage hybrid ensembles.

A peculiar type of neural network is the autoencoder, which is developed to generate new data by compressing the input in a latent space, reconstructing then the output based on the information gathered. The great advantage brought by this, is that it identified observations that would otherwise lead to large estimation errors. In conclusion, tree-based models are extensively employed in the treatment of transactional data, often obtaining better performances with respect to their neural networks counterparts whose capability increases proportionally with respect to the extent of the underlying dataset. Moreover, tree-based models allow for a more manageable training than neural networks, being easier and less time consuming to train. However, it is worth noting that even though tree-based models can be deemed more directly interpretable than neural networks, the latter are considered more appropriate in the treatment of transactional data given its highly time-dependent nature.

4. Application of AI tools in credit risk management

As mentioned, within the lending life cycle, banks are relying increasingly on AI and analytics capabilities to add value in credit decisioning, as well as in other areas of their business (McKinsey, 2021a).
However, the primary challenge lies not only in developing methodologically and technologically sophisticated models but foremost in building them so that they produce results that can be more or less easily explained to the various users of the outputs of the credit risk management models in the various fields where they are used[2]. These areas include business strategies business strategies, where the models' output must be explained both to the customers and to the credit managers; the quantification of credit losses on loans within the portfolio; and determining parameters used in computing capital requirements, as banking regulators investigate carefully the process followed by banks to compute them[3].
As highlighted in its recent survey, the Institute for International Finance (IIF, 2019) confirmed the fact that one of the main areas of application of ML techniques is credit scoring. Specifically, the survey shows that while the use of these models for supervisory reporting purposes is somewhat limited by the need to implement simple and easily interpretable models, these limitations apply to a lesser extent when the same techniques are used for management purposes. One important aspect that concerns both the "supervisory

[2] Institute of International Finance (IIF) Briefing Note (June 2021) - Explainability is a trust issue. Regulators are concerned with levels of complexity that offer limited or no insight into how the model works (i.e., so called black boxes). They want to know how models, including AI and ML, reach decisions on extending or denying credit, whether FIs have appropriate risk controls in place, and the like. A challenge of using AI/ML models is often the lack of transparency, which is imperative to building trust with customers and other stakeholders. Banks have long had to explain their decision processes to improve confidence in the robustness of a model.
[3] See CRR 575/2013, paragraph n. 179: "The estimates shall be plausible and intuitive".

reporting" and "management reporting" applications, is the integration of the traditional data used for credit risk management (e.g., credit bureaus) with other innovative data, mainly based on transactions and "point-in-time" data and information, that can improve models' accuracy.

There are many potential applications for ML techniques applied to innovative, high-frequency data.

First, they may be used in advanced early warning systems (EWS), for a prompt identification of borrowers whose behavior "tends" to reflect a potential risk, with respect to a target event which is usually a precursor of a proper default classification (i.e., 30-days delinquency, classification to IFRS9 Stage 2). While traditional systems usually require indicators based on expert opinions, ML techniques are well suited to handling large quantities of high-frequency data/updates and hence make it possible to generate effective and efficient models, with the forward-looking feature needed for EWS.

Secondly, ML techniques make it possible to capture further in advance a borrower's likelihood to transition to migrate to another stage as per the IFRS staging allocation rules.

Moreover, the competitive advantage gained from the in-depth analysis of data and high-speed processing and decision making comes from the ability to gather core information (e.g., income, consumption, etc.) from non-traditional data sources and to extract patterns that are relevant for the purposes of monitoring credit performance over a medium-term horizon, more extended the one normally in use in risk monitoring process.

Different examples of applications suggest that the common underlying idea is the purpose of combining algorithmic intelligence, to handle large quantities of data and qualitative information by saving time and costs and increasing effectiveness, with human intelligence. This combination aims to optimize credit decisions and making the credit risk management more comprehensive, fulfilling both the compliance and operating goals.

Rhzioual Berrada et al. (2022) produced a brief literature review aiming to find how AI could get benefit to the bank industry in credit risk assessment and default prediction. The authors highlight that AI methods in use for commercial banks constitute a large set of applications, as the banking industry is one of the more advanced fields using AI and machine learning. According to their analysis, feature and data preprocessing are the most important factors to be managed with the purpose to optimize algorithms and quality of the results, in terms of accuracy and precision.

Theuri and Olukuru (2022) provide a literature review regarding the application of AI in banking: they highlight that the bulk of the research is focused on credit scoring techniques, especially in consumer credit as its large growth, with particular regard to classification and the proper application of algorithms. Credit risk assessment has also been experimented with using ML. For instance, Bussmann et al. (2021) applied AI model to peer-to-peer lending platforms, with the purpose to estimate borrowers' future behaviour. Wang et al. (2020) focused the comparative assessment of several classifiers involved in ML techniques for credit scoring.

Global financial crisis, COVID pandemic, credit crunch, climate and (specifically transition) risks and other major risky conditions and scenarios have, more in general, enhanced the attention to credit risk assessment and to predicting default risk. In particular, Moscatelli et al. (2020), via the application of ML ratings, highlighted the benefits for a lender, able to offer credit to safer and larger borrowers, so that it is possible to observe a decrease in its credit losses. Estimating ML ratings involves using machine learning algorithms to analyze historical data and generate credit ratings or scores applied to borrowers. By following different steps, the process includes data collection, the selection of most relevant variables and the application of the algorithm to test models. Once the models are validated, they are integrated into the lenders' credit risk management system. This integration enables the assessment of new loan applicants or existing borrowers, assigning them credit scores or ratings based on their financial history and other relevant data.

Another portion of research is focused on alternative data sources (Roeder 2021 on public and private companies; Monk et al. 2019), to be used in addition to established credit risk indicators for supporting credit risk management. As underlined, these data sources contain important signals to identify changes in borrowers' behaviours and in their financial conditions. An example may be provided by the previously mentioned transactional data, that are particularly apt to recognize transaction patterns usually lead to insolvency.

The literature review presented by Roeder (2021) highlights that, on the one side, as expected, contributions focused on ML algorithms normally use more complex models (e.g., random forests or neural networks) to improve the quality and the accuracy of predictions, and, on the other, most of the papers suggest that variables related to alternative data provide explanatory value or improve the prediction power. There is space, also in other domains, for alternative data sources, for example in the analysis of credit worthiness of SMEs, where the datasets of information are normally smaller, especially with regards to market-based metrics.

According to the diversification in methods, we can highlight several ML and AI applications in the broad area of credit risk in banking, into different operational contexts, even if some cautions are required before a large adoption (Breeden 2020).

In terms of applications, first of all – as mentioned – ML are applied for credit scoring purposes, going ahead of the traditional statistical methods (regression analysis, discriminant analysis). Pérez-Martín et al. (2018) highlight that the increase in financial operations has led to an increase in the size of datasets: the huge volume of data and information requires new data techniques and their simulation experiments – based on home equity loans and both on traditional statistical methods, parametric and non-parametric methods and AI tools – suggest that the effectiveness of a method and, in broader terms, the final judgment about its acceptance or not is also a consequence of the major purpose of the analysis (the minimization of the mean square error, the best computational efficiency, the best response time, etc.).

Modeling corporate defaults and bankruptcies is a similar problem, even if a lower amount of data and less standardized inputs. Barboza et al. (2017) tested ML models to bankruptcy prediction and concluded that in terms of accuracy ratios these methods are better than the traditional models and, more recently, new studies applied similar techniques also to general default events, not only to bankruptcy. Nevertheless, ML models are not perfect, because the risk of misclassification, the more computational process time required and also the fact that extensive datasets are not common. Moreover, the author points out that additional research is needed with regards the use of macroeconomic variables as explanatory variables in ML models, by combining these external data with firm-specific data and information.

Van Thiel and van Raaij (2019) tested experiments about AI credit risk models for probability of default in consumer lending: their findings put in evidence as AI techniques performed better than traditional models. Default prediction improves in accuracy if lenders can access to effective and/or estimated income, spending data and create relations between economic/financial data and social media data.

4.1 The integration between traditional and AI models

The increase in the availability of data, new and sophisticated analytical techniques, and customers' rising expectations of a complete digital experience are key factors, that are increasingly crucial to market success of nowadays financial firms. The models adopted by banks to estimate the probability of default of their counterparties are also evolving to make most of these opportunities, by exploiting internal and proprietary data sources to the bank not yet used, new data sources including those outside the bank, and new ML algorithms.

As mentioned, innovative data, such as current account transaction or data extracted from social networks, are increasingly included in Credit Risk models through one or more specific ML modules operating along with "traditional" modules which generally cover established information areas (e.g., socio-demographic, financial, banking behavior, qualitative assessment). Such integration of traditional modules with ML modules led to the development of high-performance models capable of rapidly capturing phenomena and signals that traditional models find more difficult to intercept. Crosato et al. (2021), for instance, analyzed the use of online indicators from firms' websites to predict firms' default and borrowers' creditworthiness in the banking sector.

Some brief experiences, in which the traditional module has been integrated by an ML module employing alternative techniques and data, worth a mention.

The first example consists in the implementation of a transactional module capable of discriminating the riskiness of companies by looking at trends in the payment of salaries, correctly penalizing the score of those companies having irregular salary payments, whereas positively score those companies having seasonal business activities – e.g. agricultural enterprises - hence seasonal salary payments. Another practical case concerns the identification of counterparty risk during the Covid-19 crisis, in which the transactional score proved to be extremely reactive in identifying changes in the riskiness of borrowers: in a real-life case the transactional score remained stable during 2019, rapidly grew after February 2020, when the social restrictions were introduced and began falling after June 2020 when the restrictions were eased. A further practical application for a transactional module could be the implementation of an early warning system due to the long prediction horizon of transactional information, capable also of detecting signs of credit quality deterioration that had not occurred before. Another practical case involves employing a random forest algorithm to detect default within 12 months of loan origination. Such methodology yields more predictive results compared to the traditional logit model, despite possible problems in terms of interpretability of the results.

As already mentioned, stand-alone AI models may be used to supplement more traditional modelling techniques. Han et al. (2013) provided an example of this integration, in the case of employing traditional models to select the relevant drivers, which may then be reprocessed and combined in the final model using advanced algorithms. In this way, the traditional models are the first "filter" that excludes variables that are highly correlated or not meaningful from a statistics or credit perspective, whereas alternative methods are used to develop the model. Another way of using two techniques jointly could be the creation of a function integrating the output of a traditional model with the output of one or more ML models. With this approach, it is assumed that various algorithms can more accurately model the different aspects or sub-areas of the phenomenon in question and that their interaction might bring out the "best" of the various approaches.

A third possibility consists of integrating traditional and innovative models with an expert, rather than statistical, approach. For example, this could happen using a notching matrix, adjustments or overrides of the outputs of the traditional model, particular in those sub-areas where the predictive power is weakest. At the same time, there may be instances in which traditional models and alternative models lead to convergent predictions and other instances in which the predictions are divergent or inconclusive, enabling the analyst to focus the expert valuation on the later.

Moreover, AI models can be used to correct prediction errors committed with traditional models.

Integrating traditional models with alternative AI-based methodologies in one of the ways described above may offer a series of advantages over using a stand-alone AI model. First, this choice may be a gradual transition towards adopting more advanced methodologies, combining modelling techniques that are now consolidated in market practice with more innovative solutions, thereby preserving the interpretability of the model's outputs, especially for internal users of rating models like loan managers and credit analysts. The integration approach might also be the easiest solution in the medium term for banks that use internal models not only for management reporting purposes but also for supervisory reporting since, in this case, the models must be formally approved by the regulator. To this end, combining traditional models with AI models can guarantee more comparable results or make it possible to quantify and compare the extra performance of the AI modules with the model's overall discriminative capacity. Similarly, this approach leaves a certain degree of flexibility in its design, in that it does not preclude the possibility of "dismantling" the AI component to apply, if necessary for the individual use cases, only traditional models. However, the decision to integrate these types of models may give rise to unknown variables. Certainly, this choice implies the need to estimate several models (both traditional and alternative) and entails the identification of the most appropriate integration methodologies, requiring inevitable extra efforts for risk management units, not to mention the potential complexities of the deployment phase when they are taken from the test environment and implemented in the bank's legacy systems.

Finally, the decision to apply an integration approach may, in certain cases, reflect a compromise that, for extremely non-linear phenomena that need to be modelled, could lead to a dull performance compared to a purely AI-based model.

4.2 Use of AI models for the validation of traditional models

Going beyond the integration, another relevant point concerns the use of AI models for validation and benchmarking of traditional models.

The banking regulation on one hand, and the supervisory practice on the other one, concur to set quite high standards to the validation practice banks have to adopt, especially for the most sensitive models, i.e. those used for computing capital charges or for setting the loan loss provisions. In these cases, validation teams must challenge internal models before they are put in production and afterwards, along their entire life cycle.

Such a regime calls for continuous advancement of the validation practice even making use of ML techniques to develop challenger models capable to single out the weaknesses of the more traditional ones.

In this regard examples exist of cases where ML models have been used to validate IRB models, i.e. models used for capital computation purposes, once authorized by the competent banking supervisory authority (Aifirm, 2022; Locatelli, Pepe, Salis (eds.) 2022). A first example pertains to the usage of ML techniques to identify any relevant bias in the ranking yielded by a corporate rating model. More in detail, the analysis was conducted by comparing the estimates resulting from the concerned model, based on traditional statistical methods (i.e. logistic regression), and those produced by ML approaches (decision trees, random forests, neural networks), leaving unchanged both the training set data (including the time horizon) and the explanatory variables. The results were assessed using established materiality thresholds of divergence and no significant differences arose, suggesting a negligible model risk.

A second example refers to a retail rating model, again developed using the traditional logistic approach. To this aim the validation team developed an alternative ML model, combining modules developed with traditional statistical techniques with other realized using ML techniques. In the latter case specific methodologies were employed to select and handle the explanatory variables, consistently with the ML techniques. It emerged a challenger rating model whose performances have been compared to those of the main model in-sample and out-of-sample/out-of-time. The comparison showed the accuracy of the alternative model, which was submitted to the regulatory validation in lieu of the original one.

ML models are also used for validating models used for management reporting purposes; even in this case different case studies can be briefly summarized. For example, the application of scoring models developed with ML techniques to challenge expert credit scoring and, more in detail, to measure the customer's riskiness over a short-term horizon (e.g., six months). The model was developed to provide a risk assessment of borrowers during Covid-19 period and is distinctly point-in-time. This entailed the use of a long list of variables fed by multiple sources, such as financial statements, transactional data, credit bureau data, industry data, etc. The model was employed to challenge the specific assessments provided by the bank's credit managers, assessing the borrowers' resilience after the impact of the pandemic.

Another example concerns the development of a ML model used to challenge the PD retail rating model used for computing the loan loss provisions according to the IFRS9 accounting principle. To this aim an artificial neural network model (of the deep learning variety) was developed to challenge the in-production rating model, estimated using a logistic regression. Despite utilizing the same set of variables for training both models, the neural network required a pre-processing phase to normalize the categorical variables.

The time horizon on which the two models have been trained was different, as in the case of the challenger model more recent data have been used. Therefore, the two models have been put in production to assess the concerned portfolio at the same date. For the purposes of the comparison, standard performance indicators (Cap Curve and Accuracy Ratio, Roc Curve and AUROC (AUC), Confusion matrix) have been used. It emerged that the in-production model shows performances just below those of the challenger model.

The negligible difference between the performance of the two models confirmed that the in-production model's got good predictive power and accuracy and, therefore, was suitable to be used to compute the expected credit losses in accordance with IFRS 9.

AI techniques used for validation, testing and benchmarking purposes have now become general operating practice to the same degree as ordinary validation techniques with respect to managerial models and boast excellent performance even though they are still continuously evolving. They are, however, less frequently used for models aimed for computing capital charges due to the greater regulatory constraints, although in recent years the regulator has incentivized their use to make the validation practices more challenging.

5. Evolution and new challenges in AI models

5.1 The financial services regulatory framework: some open questions

The regulatory landscape for credit risk and decisioning is becoming increasingly more complex. There are a huge set of laws and regulations that financial institutions are required to respect. First, we refer to specific bank regulation, for example Capital adequacy

requirements (since Basel II), but also credit provisioning and accounting (IFRS 9 and 17). Second, privacy rules (GDPR) and anti-discrimination acts are relevant (e.g. EU Artificial Intelligence Act and Consumer Credit Protection Act).
As highlighted previously, over the past decade, the use of alternative models and data have disrupted the existing credit risk processes within banks and lending institutions. Despite the evident benefits and enhancements, these advancements also bring forth several challenges, introducing new risks and potential drawbacks. As a consequence, there is an increasing scrutiny around these tools, leading to increased attention and monitoring from regulators. The framework is not homogeneous: regulatory requirements is largely still under development.
In November 2021, the European Banking Authority (EBA) released a discussion paper with the purpose to understand the challenges and opportunities coming from machine learning (ML) tools to be applied in the context of internal ratings-based (IRB) models to calculate regulatory capital for credit risk.
EBA recognizes that ML models are more complex than traditional modeling techniques such as regression analysis or simple decision trees, and often they lack in transparency, but they can count on large data availability and increased storing capacity. It's worthy to mention that some issues, such as data usage and explainability, are not entirely novel in managing IRB models, but advanced techniques may lead to new challenges or even to some "black box" models that may create difficulties in interpreting the results and in the understanding by the management functions (EBA, 2021). For these reasons, EBA provided a set of recommendations to favour an appropriate use of ML/AI techniques, the coexistence with other models and to contribute to improve the harmonization of rules about capital requirements across Europe.
According to the IIF 2019 report, ML finds its most common application in credit risk within the realms of credit decisions/pricing. However, its use in IRB models is more restricted, primarily serving as a complement to standard models. For example, ML techniques can provide "model validation", data quality analysis, selection and construction of explanatory variables. At the same time, it is worthy to highlight the trade-off between predictive power and interpretability. This trade-off also explain why the adoption of ML tools for managerial decisions in credit risk management is more straightforward *vis à vis* their application in areas subject to the regulatory scrutiny. This is due to the strict regime supervisors have imposed on these models, emphasizing the need for both predictive accuracy and comprehensibility.
EBA also recognizes that the use of ML techniques within the IRB framework might add value, if some recommendations about adequate monitoring, validation and explainability are ensured. First of all, all the stakeholders involved should have an appropriate level of knowledge of the model's functioning; financial institutions have to avoid unnecessary complexity in the modelling approach. Furthermore, the model has to be correctly interpreted and understood, especially in the case a human judgement is required, and regular updates need to be analyzed and justified, even though the framework for credit risk is typically stable.
A specific issue is posed with regard to "representativeness" and "data quality" issues, because of the direct relationship between models' performances amount and quality/representativeness of the training data. According to EBA's guidelines, financial institutions, must ensure sufficient data quality, especially in the case external and/or unstructured data are included in the models, with the purpose to guarantee accuracy, completeness and appropriateness of the data.
The European Banking Federation (EBF) on September 2021 released a position paper on the EC proposal for a regulation laying down harmonized rules on artificial intelligence (AI Act).
Among other comments, EBF poses special attention on the importance of insuring consistency in supervisory expectations and practices among different national competent authorities. A "level playing field" must be ensured: in the case the same AI application is used by different entities thar are supervised by different Authorities using misaligned approaches, this principle would be broken. "Same activity, same risks, same rules" principle must be guaranteed.

5.2 Explainability and interpretability of AI algorithms

Machine learning and AI present some unique challenges to application in credit risk and the growth in terms of "quality" of the methodologies and innovative applications has very been very significant in recent years.
The use of AI models generally produces performance results expressed, for example, in terms of accuracy, that tend to surpass those observed for classic models based on parametric estimates (e.g., logit/probit).
However, the accuracy can also cause greater methodological complexity, which asks higher attention on the interpretability and usability of AI models by the various stakeholders. This concern can be relevant both for "management" purposes, such as employing the model to support decision-making, and for supervisory reporting. Interpretability, in the context of decision-making processes highlights an important connection with the concept of robustness or stability, the ability of retaining good predictions also in case of unexpected situations.
Interpretability and stability are generally deemed crucial features associated with a model in the context of its use in decision-making processes, because while interpretability relates to the use of models in predictable conditions, stability provides information on how the model will behave in unexpected situations.
Accuracy and quality data are also crucial, but not sufficient. The guidelines established in the Fair Credit Reporting Act, concerning consumer protection and his privacy and security set that lenders cannot discriminate against protected classes and that consumers receive explanations in the case of denial of credit. So, the question is about the ability of ML techniques to avoid these discriminations, and other similar concerns in model risk management must be solved before a large adoption of these techniques (Breeden 2020).

This specific issue can be also linked to the "explainability": the result of the credit worthiness' analysis has to be understandable by the consumer, so that in the future he can make improvements in his financial situation to be "eligible" in the case of a future credit application.

One of the main objectives set forth in the regulatory framework on AI proposed on 21 April 2021 by the European Commission focuses on resolving and lessening problems related to the governance of risks deriving from AI applications. The proposal aimed to implement the development of an ecosystem of trust by proposing a legal framework for trustworthy AI, to increase confidence in AI-based solutions that can improve human well-being (European Commission 2021). As the presence of a number of risks, a series of indicators could be required to comply with specific trustworthy principles like accuracy, robustness, fairness, efficiency and explainability and making AI more trustworthy and, more in detail, precise, stable inclusive, efficient, and explainable (European Commission, 2021; Locatelli et al., 2022).

Based on the new requirements highlighted in the European Commission's proposed regulatory framework on AI, current and future research will focus increasingly on the operating effectiveness of key principles for trustworthy.

Among others, a special focus on explainability or interpretability deserves a mention. As remarked by Hamon et al. (2020), AI is becoming a key technology in automated decision-making systems based on personal data, with a potential and significant impact on the fundamental rights of individuals. In this context, the General Data Protection Regulation (GDPR), in force since 2018, has introduced a set of rights that relate to the explainability of AI and the right of any individual to ask for an explanation of the decisions taken on her application.

As already mentioned, the use of AI models generally yields more accurate performance outcomes compared to traditional statistical models reliant on parametric estimates, such as logit/probit models.

In 2018, the European Commission published a document containing ethics guidelines for AI, prepared by a group of AI experts (European Commission, 2018). In this document, the European Commission described the explainability and interpretability of AI algorithms as fundamental requirements for trustworthy AI.

In June 2023, European Parliament adopted the final text and amendments on the proposal for harmonized rules on artificial intelligence (so called "Artificial Intelligence Act"). According to the final text, AI systems used to evaluate the credit score or creditworthiness of individual are required to be classified as "high-risk AI systems", because the impact of these decisions on his/her financial resources, spending decisions and access to essential services (European Parliament, 2023). The proposal also highlights the importance of the risk of discrimination as a possible but unintentional "output" of the AI systems towards vulnerable individuals or groups.

More developments in research and practice are expected to tackle this risk, as the disparate impact can also be a subtle phenomenon, both in avoiding and in detecting it (Skanderson, 2021). The consequences of the applications of AI tools in the financial industry are still largely unknown and difficult to foresee. The progress in European regulation aiming to establish a uniform legal framework ant to regulate AI systems in accordance with the values and fundamental rights of the European Union is a crucial point (Visco, 2023).

Also, the European Central Bank (ECB) has demonstrated a clear awareness of the usefulness of AI approaches in credit risk management and it encouraged banks to use all the available data – especially unstructured data – to appreciate borrowers' creditworthiness, also by including forward-looking elements and instant data in these analyses. This development is a required course of action for credit risk analysis but, at the same time, an open challenge for the next future is about the way by which the AI-based models that use unstructured data will replace traditional approaches and information or if they will supplement them, making them more predictive and responsive to context changes.

Since, most likely, the solution will vary depending on the purpose of the credit analyses, one clue might be the role that instant economics analyses are filling with respect to economic predictions. In this regard, a perception is emerging that while the approaches based on high-frequency data are extremely useful in rapidly capturing turnarounds in the economic cycle, they meet with more difficulties when they are used to precisely quantify the level of activity. In this field, traditional techniques maintain a competitive edge because of the higher quality of official statistics.

Similarly, it is plausible that traditional models are likely to maintain a place in credit risk analysis, as AI-based models progressively support them in fields where they are superior in connection with the type of information to be processed and the speed with which they make use of this information. A key element to bear in mind in this structural credit risk modelling change relates to all cases in which AI techniques are applied to aspects impacting human life. Preserving ethics and ensuring transparency remains a pivotal consideration across all AI applications.

References

Aifirm, Artificial Intelligence e credit risk. Possibili utilizzi di metodologie e dati alternativi nei sistemi interni di rating [it], Position Paper n. 33, 2022

Altman, E.I., Sabato, G., & Wilson, N., The value of non-financial information in small and medium-sized enterprise risk management, J. Credit Risk 6 (2), 2010

Anderson R.A., Credit Intelligence and Modelling: Many Paths Through the Forest of Credit Rating and Scoring. Oxford University Press, 2022

Angelini E., di Tollo G. and Roli A., A neural network approach for credit risk evaluation. The quarterly review of economics and finance, vol. 48, n. 4, pp. 733-755, 2008

Baesens B., Van Gestel T., Viaene S., Stepanova M., Suykens J. and Vanthienen J., Benchmarking state-of-the-art classification algorithms for credit scoring. Journal of the Operational Research Society, vol. 54, n. 6, 2003, pp. 627–635

Balogh, S., & Johnson, C., AI can help reduce inequity in credit access, but banks will have to trade off fairness for accuracy—For now. Insider.com, 2021

Barboza F., Kimura H., Altman E., Machine learning models and bankruptcy prediction, Expert Systems with Applications, Volume 83, 2017

Bequé A. and Lessmann S., Extreme learning machines for credit risk: An empirical evaluation. Expert Systems with Applications, 86, 2017

Berg T., Burg V., Gombović A. and Puri M., On the Rise of FinTechs – Credit Scoring using Digital Footprints, NBER Working Papers 24551, 2018

Breeden J., A Survey of Machine Learning in Credit Risk, 2020, DOI:10.13140/RG.2.2.14520.37121

Bussmann N., Giudici P., Marinelli D., and Papenbrock J., Explainable machine learning in credit risk management, Computational Economics, 2021, vol. 57, n. 1, pp. 203-216

Capital Requirements Regulation (CCR), Regulation (EU) No 575/2013 of the European Parliament and of the Council of 26 June 2013 on prudential requirements for credit institutions and investment firms, 2013

Carmona, P., Climent, F., & Momparler, A., Predicting failure in the US banking sector, International Review of Economics and Finance, 61, 2019

Crosato, L., Domenech, L., & Liberati C., Predicting SME's default: Are their websites informative?, Economics Letters, 204, 2021

Crosato, L., Domenech, L., & Liberati C., Websites' data: a new asset for enhancing credit risk modeling, Annals of Operations Research, 2023

Deloitte, Artificial Intelligence for Credit Risk Management, April, 2020

Di Biasi P., Gnutti R., Resti A. and Vergari D., Machine learning per il rischio di credito: quale ruolo nei modelli regolamentari? [it], in Bancaria, n. 5/2022

EBA, Report on Big Data and Advanced Analytics, January, 2020a

EBA, First evidence on the use of moratoria and public guarantees in the EU banking sector, Thematic Note EBA/Rep/2020/31, November, 2020b

EBA, Discussion Paper on machine learning for IRB models, November, 2021

ESMA, Artificial intelligence in EU securities markets, February 2023

European Commission, Ethics Guidelines for Trustworthy AI, June 2018

European Commission, Regulation of the European Parliament and of the Council laying down harmonised rules on artificial intelligence (Artificial Intelligence Act) and amending certain Union legislative acts, April 2021

European Parliament, Artificial Intelligence Act, Amendments adopted by the European Parliament on 14 June 2023 on the proposal for a regulation of the European Parliament and of the Council on laying down harmonised rules on artificial intelligence (Artificial Intelligence Act), Texts Adopted, June, 2023

Experian, Experian Study on Credit Decisioning and Alternative Data Use, 2022

Financial Stability Board, Artificial intelligence and machine learning in financial services. Market developments and financial stability implications, 1, 2017

FitchSolutions, Credit risk, data and AI. Managing spiralling demands and delivering value, 2022

Giudici P., Raffinetti E., Shapley-Lorenz eXplainable Artificial Intelligence, Expert Systems With Applications, Expert Systems With Applications, volume 167, issue 14, p 104, 2021, https://doi.org/10.1016/j.eswa.2020.114104

Giudici P., Centurelli M. and Turchetta S., Measuring AI SAFEty, 2023, available at https://ssrn.com/abstract=4450731

González-Fernández M. and González-Velasco C., An Alternative Approach to Predicting Bank Credit Risk in Europe with Google Data, Finance Research Letters, vol. 35, 2019

Gül S., Kabak Ö. and Topcu I., A Multiple Criteria Credit Rating Approach Utilizing Social Media Data, Data & Knowledge Engineering, vol. 116, 2018, pp. 80-99

Hamon, R., Junklewitz, H., Sanchez, I. Robustness and Explainability of Artificial Intelligence - From technical to policy solutions, EUR 30040, Publications Office of the European Union, Luxembourg, Luxembourg, 2020, ISBN 978-92-79-14660-5 (online), doi:10.2760/57493 (online), JRC119336

Herrmann H. and Masawi B., Three and a half decades of artificial intelligence in banking, financial services, and insurance: A systematic evolutionary review, Strategic Change, vol. 31, 2022, pp. 549-569

Institute of International Finance, Machine Learning in Credit Risk, 2019

Institute of International Finance, Explainability is a trust issue, Briefing Note, June, 2021

Khandani A. E., Kim A. J. and Lo A. W., Consumer credit risk models via machine learning algorithms, Journal of Banking & Finance, vol. 34, n. 11, pp. 2767-2787

Koyuncugil A.S. and Ozgulbas N., Financial early warning system model and data mining application for risk detection, Expert systems with Applications, vol. 39, n. 6, 2012

Lessmann S., Baesens B., Seow H.-V. and Thomas L. C., Benchmarking state-of-the-art classification algorithms for credit scoring: An update of research. European Journal of Operational Research, vol. 247, n. 1, 2015, pp. 124-136

Locatelli R., Pepe G. and Salis F. (eds)., Artificial Intelligence and Credit Risk, Palgrave Macmillan, 2022

McKinsey & Company, AI-powered decision making for the bank of the future, March, 2021a

McKinsey & Company, Designing next-generation credit-decisioning model, December, 2021b

Mhlanga D., Financial Inclusion in Emerging Economies: The Application of Machine Learning and Artificial Intelligence in Credit Risk Assessment, International Journal of Financial Studies, 2021, vol. 9., n. 39, https://doi.org/10.3390/ijfs9030039

Monk A., Prins M., and Rook D., Rethinking Alternative Data in Institutional Investment, The Journal of Financial Data Science, 2019, Winter, pp. 14-31

Moscatelli M., Parlapiano F., Narizzano S., and Viggiano G., Corporate default forecasting with machine learning, Expert Systems with Applications, 2020, vol. 161

Nalić, J., Martinović, G., & Žagar, D., New hybrid data mining model for credit scoring based on feature selection algorithm and ensemble classifiers, Advanced Engineering Informatics, vol. 45, 2020

Odinet C.K., Fintech Credit and the Financial Risk of AI, in Cambridge Handbook of AI and Law (Kristin Johnson & Carla Reyes eds., 2022), University of Iowa Legal Studies Research Paper No. 2021-39, available at SSRN: https://ssrn.com/abstract=3917638

Onay C. and Öztürk E., A Review of Credit Scoring Research in the Age of Big Data, Journal of Financial Regulation and Compliance, vol. 26, n. 3, 2018, pp. 382-405

Pérez-Martín, A., Pérez-Torregrosa, A., & Vaca, M., Big data techniques to measure credit banking risk in home equity loans. Journal of Business Research, 89, 2018

Imane Rhzioual Berrada I., Barramou F.Z. and Bachir Alami O., A review of Artificial Intelligence approach for credit risk assessment, 2022, “2nd International Conference on Artificial Intelligence and Signal Processing (AISP)”, DOI: 10.1109/AISP53593.2022.9760655

Roeder J., Alternative Data for Credit Risk Management: An Analysis of the Current State of Research, 2021, BLED 2021 Proceedings

Safi R. and Lin Z., Using Non-Financial Data to Assess the Creditworthiness of Businesses in Online Trade, Proceedings of the 18th Pacific Asia Conf. on Information Systems, Chengdu, China, 2014

Schapire R.E., The boosting approach to machine learning: An overview, Nonlinear estimation and classification, 2003, pp. 149-171

Skanderson D.M., Managing Discrimination Risk of Machine Learning and AI Models, ABA Journal of Labor & Employment Law, vol. 2, 2021

Theuri J. and Olukuru J., The impact of Artificial Intelligence and how it is shaping Banking, Kenya Bankers Association (KBA) Centre for Research on Financial Markets and Policy, Working Paper Series, 2022, WPS/07/22

Van Thiel D. and Van Raaij W.F., Artificial intelligence credit risk prediction: An empirical study of analytical artificial intelligence tools for credit risk prediction in a digital era, Journal of Risk Management in Financial Institutions, 2019, vol. 12, n. 3, pp. 268-286

Visco I., Intervento del Governatore della Banca d’Italia [it], Italian Banking Association, Rome, July 5th, 2023

Wang, Y., Zhang, Y., Lu, Y., & Yu, X., A comparative assessment of credit risk model based on Machine Learning – A case study on bank loan data, Procedia Computer Science, vol. 174, 2020

West D., Neural network credit scoring models, Computers & Operations Research, vol. 27, n. 11-12, September, 2000, pp. 1131-1152

Yang S., Liu Z. and Wang X., News Sentiment, Credit Spreads, and Information Asymmetry, North American Journal of Economics & Finance, vol. 52, 2020

Zensar Technologies, The Case for Re-inventing the Credit Decisioning Approach

Zhang Z., Gao G., and Shi Y., Credit risk evaluation using multicriteria optimization classifier with kernel, fuzzification and penalty factors. European Journal of Operational Research, vol. 237, n. 1, pp. 335-348

Zhu, Y., Zhou, L., Xie, C., Wang, G.-J., & Nguyen, T. V., Forecasting SMEs’ credit risk in supply chain finance with an enhanced hybrid ensemble machine learning approach. International Journal of Production Economics, 2019