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# CUSTOMER CREDIT WORTHINESS IN THE DIGITAL AGE: A MANAGEMENT APPROACH TO MACHINE LEARNING APPLICATION IN BANKING

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A B S T R A C T

*This study investigates the shift in private banking from conventional creditworthiness assessment to advanced machine learning (ML) models. Employing a synthesis technique, this study conducts a review of literature and case studies and highlights how ML models, through the integration of alternative big data and advanced algorithms, can enhance accuracy in forecasting customer defaults and contribute to financial inclusion. The research underscores legal and ethical concerns regarding alternative data processing, necessitating thorough compliance checks by banks and regulatory authorities. Furthermore, it underlines the necessity for banks and regulators to develop technical skills to ensure ML models remain transparent and understandable, avoiding the pitfalls of becoming "black boxes". Future research is suggested to explore risk mitigation strategies based on its ML deployment approach, technical aspects of ML algorithms, and the impact of ML-based credit scoring on broader macro-financial linkages.*



## 1. INTRODUCTION

In the rapidly evolving landscape of digital technologies companies are undergoing digital transformation. Digital transformation encompasses more than digitalization or digitization of documents (Schallmo & Williams, 2018). In the academic literature, digital transformation transcends mere digitization, which typically involves converting objects into digital formats, often seen with paper documents. Digitalization, by contrast, refers to integrating business processes into the digital domain, while digital transformation implies a broader range of changes within the organization. It encompasses not only the adoption of new technological tools but also significant alterations in work practices and organizational culture. In other words, it involves changes not only in the new technological tools used for performing the job but also in the logic and problems of the work process itself. This paradigm shift is rooted in the "first principles" (Brett, 2019) approach of digital transformation, which necessitates revisiting and reviewing existing operations and, where necessary, undertaking revolutionary changes. Digital transformation aims to maximize

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companies' efficiency and strives for data-driven decision-making. It is essential to distinguish between the changes that have in their core the "first principles" approach from those following a "design by analogy" approach, where business processes are modified, albeit non-disruptively, to improve existing procedures. In the digital era substantive, long-term value is anticipated from changes driven by the "first principles" approach, potentially leading to a profound transformation in the very logic of the business processes.

The banking sector, which occupies a prominent place in the financial system, comprises the central bank (sometimes referred to as the national bank), along with the public and private banks. The banking sector is also embracing digital technologies, and it often collaborates with technological companies to ensure a smooth transition into digital transformation. The primary goal of private banks (hereinafter banks) is the maximization of profit. Banks primarily engage in deposit intake and loan issuance to customers, with the latter encompassing credit risk – the risk associated with borrowers' potential default on loans, when the borrowers fail to repay their loans. In pursuit of profit optimization, banks strive to reduce credit risk through credit risk management. To this end, they implement credit risk scoring systems, which utilize customer data as input and return the client's creditworthiness score. Globally, many banks use the widely recognized "FICO" scoring system (Hayes, 2023). Nonetheless, some banks may also develop their own scoring systems, which are basically econometric models, that return creditworthiness scores (or the probability that the loan would be repaid). It should be noted that previously, under Basel II, which permitted internal rating-based (IRB) models for credit risk assessment, there were frequent instances of risk underestimation, often due to insufficient or absent historical data. In today's digital era, the integration of big data and ML is anticipated to enhance the effectiveness of these IRB models, thereby ensuring more accurate credit risk assessments aligned with Basel III standards. It is important to note that assets containing credit risk (in risk-weighted total assets) are predominant in both volume and volatility within banks.

Using Machine Learning (ML) in their credit scoring systems, banks aim to enhance the predictive power of their models (Wang et al., 2020). However, the application of ML in credit risk assessment systems may introduce not only improvements but also some novel challenges. Such challenges may include ethical and legal issues regarding customer data processing, which may hinder the ability of the bank to leverage innovative technologies like ML in their business processes. Moreover, ML-based creditworthiness assessment models may result in potentially discriminative algorithms leading to reputation and compliance risks for banks. Apart from the mentioned issues, it cannot be neglected that other risks may arise based on future evolutions, bank-specific factors and ML deployment approaches.

Therefore, in the context of digital transformation, private banks planning to apply ML models need to counterbalance the related risks with adequate risk mitigation actions and assess overall impact of ML application. Consequently, the study aims to bring these components together, after which banks can assess the advantages of ML application against the related residual risks, which is the inherent risks' impact reduced by mitigation actions.

## 2. METHODS AND DATA

In this study, we employ a synthesis methodology to combine various elements: firstly, we identify the advantages of implementing ML in creditworthiness assessment to underscore its importance, secondly, we examine the associated risks to ensure that banks comprehensively understand the inherent risks involved in ML applications, and thirdly, we explore potential risk mitigation strategies, drawing from both academic literature and international best practices. We present the outcomes of this synthesis in tabular format.

ML has been employed in banking systems from an early stage, and one of its primary applications is in risk management, which can significantly reduce banks' expenses. One of the relevant studies shows that cutting credit lines based on forecasts using ML techniques can save up to 25% losses (the study used a bank's customer data (transaction amounts, credit bureau data, and account-balance data) spanning from 2005 to 2009) (Khandani et al., 2010).

As already noted, credit risk is a major risk area for banks, and not surprisingly the application of artificial intelligence and ML in credit risk is most thoroughly studied compared to other bank risks (Leo et al., 2019). A variety of ML algorithms are employed for a diverse range of applications, indicating the absence of a singular "best" algorithm for credit risk assessment models. Notably, algorithms like SVM (support vector machine) and Random Forest tend to be more prevalent in academic studies. Apart from the credit scoring models, the application of ML is also beneficial for modeling IFRS 9 expected credit loss calculation's components, such as EAD (exposure at default), PD (probability of default), and LGD (loss given default). Another study demonstrates that ML is applied in various aspects of credit risk assessment, ranging from the most common application in scoring systems to credit risk stress testing (Milojević & Redzepagic, 2021). A study based on data from China concludes that "Random Forest" was the most effectively performing algorithm for the particular case. However, the effectiveness of the model varies with the data and ultimately requires evaluation after the loan maturity date to ascertain repayment status (default or nondefault). Moreover, it is suggested not to limit the comparison of different ML algorithms to a single metric (which is usually AUC - Area Under Curve), but also to consider other indicators, such as RMSE (root mean square error), AIC (Akaike information criterion), Gini, etc. (Addo et al., 2018). In addition, F-score, which combines the recall and precision qualities of the given model, could also be used as a comparison criterion.

Besides the credit bureau data (the term "traditional data" will be used interchangeably for credit bureau data), ML models imply the processing of alternative data, which is big data about the customer to be analyzed by ML models. A study demonstrates that "digital footprint" data, gathered when customers interact with online stores, can nearly match the traditional credit bureau data for the assessment of customer creditworthiness (Berg et al., 2018). In that study, alternative data consisted of a dozen parameters about the customers, like device type (computer, laptop, mobile, etc.), operating system (iOS, Android, etc.), Email hosting email providers (Gmail, Yahoo mail, etc.), channel of accessing the platform, check-out time, the "do not track" setting activation status, and dummy variables, like whether the email contains the individual's name (positive impact on the creditworthiness forecast) or a number (negative impact) or whether the customer failed to fill the email correctly the first time when entering the platform. In the developed model these variables are regarded as proxies related to customers' future repayment behavior. For example, the study finds that customers have enter the online shop from price comparison sites have higher default rates than those who come through search engine ads, which is also supported by marketing studies on impulse shopping personality traits. Similarly, those clients who have their names in their email addresses are significantly less likely to default compared to those who did not include their names in their email addresses. As we can notice, even the small details on customers that are collected during their online visit (in this case to an online shop) can serve as an informative base on their future financial behavior. However, it is to be noted that the study emphasizes the role of the alternative data not as a substitution of the credit bureau data but rather as a complementary source of data. The reason was that there was only a small positive correlation (10 %) between the alternative and the traditional data, implying that together they could lead to a far better model. Thus, the discriminatory power (the ability to distinguish between the defaults and non-defaults) of the model increased when combining both datasets and its AUC was about 5% higher than that of a model with solely credit bureau data. Thus, the study shows also that the integration of alternative data with traditional data enhances the model's efficiency. However, it should be taken into consideration that the study was conducted on data from Germany for the period of 2015-2016 and that these correlations may not be universally applicable, varying significantly across different countries and banks.

Yet, even though the "digital footprint" data is easily accessible for online shops at almost no cost (when the customer hits the "accept cookies" button, the site collects customers' data), its integration into bank credit scoring models poses legal challenges in data transfer and processing. This is where banks could face legal and ethical issues. The possible solutions to the problems regarding the integration of alternative data into credit scoring models are explored afterward.

For potential borrowers lacking a preliminary credit history, the processing of alternative data with ML can become a game changer, promoting financial inclusion for underserved and currently "unbanked" individuals. This is shown by another study on alternative data, which found that 30% of the organizations (SMEs) in their sample (the study builds on data that Argentinian bigtech Mercado Libre possesses) classified as "high risk" based on credit-bureau data were regarded creditworthy when assessed by a system using ML and alternative data (including their sales volume on online platforms, ratings, industry-specific data, and other data accessible from social networks and other sources) (Frost et al., 2019). In other words, the mentioned 30% would have been unjustly denied to receive a loan based on models operating solely on credit bureau data, despite their potential to repay the loan (which would not have been possible to reveal due to the absence of credit history). The main reason why so many SME companies are excluded from the opportunity to benefit from financial services is that most of those companies to need have required reliable financial information (for example, financial statements with reliable external audit opinion) needed for credit risk assessment under current conventional credit risk assessment systems. Therefore, even SMEs with substantial online revenue streams would fall outside the eligible borrower category. On the other hand, bigtech companies (which are big technological firms that are engaging in the financial service business) may have large datasets on those companies who have transactions in their online platforms (i.e., Alibaba, Amazon, Mercado Libre). This study also suggests that the big data with ML techniques can facilitate financial inclusion by allowing more SMEs to get credit. However, the ultimate comparison between ML-based scoring systems versus the more traditional ones requires further analysis of the same sampled SMEs through the financial and business cycle. In other words, whether the observed 30% otherwise rejected SME customers would have lower probability of default or not, can be observed only after the loan maturity end date.

Machine learning applications help in reducing information asymmetry allowing banks to assess creditworthiness without direct access to a borrower's complete financial data and thus diminishing the need for a loan collateral (Gambacorta et al., 2020).On the other hand, the study shows that lower collateral would mean that previously secured loans are no longer connected to the asset prices in the region and cause changes in macro-financial linkages (specifically, weakening the financial accelerator mechanism).

Moreover, in comparison with the transparent conventional credit risk assessment systems, the use of ML algorithms can lead to the creation of "black box" models (Leo et al., 2019), which can become intractable in terms of identifying the main factors used in decision-making of loan issuance. The regulator (Central Bank) must pay attention to the approach used in credit risk assessment, ensuring the transparency of the algorithms used and eliminating potential discriminatory biases (Addo et al., 2018) and fraud risks.

This holistic approach to employing ML and alternative data in credit risk assessment demonstrates its revolutionary potential, especially in advancing financial inclusion for individuals lacking formal credit histories. It underscores machine learning's capacity to address information asymmetry issues, while concurrently emphasizing the imperative for regulatory oversight to guarantee both transparency and fairness in its application.

## 3. RESULTS AND DISCUSSION

The points taken from academic literature and international best practice are summarized in Table 1.

### 3.1. Deployment approaches

First, it's important to understand how ML systems are being integrated into banks for the evaluation of client creditworthiness. There are generally two approaches: through internal capabilities or via external collaboration. In the majority of banks, the existing IT and technical expertise of the workforce fall short of the autonomous development of ML systems, often necessitating a significant time investment (T. Simonyan, personal interview, November 17, 2023). As with other digital transformation projects, banks may prefer to collaborate with companies introducing innovations in financial technology, such as fintechs and bigtech firms (Meta, Google, Apple, Amazon, etc.). Fintechs, being technology companies, possess the required technical skills for developing and implementing ML systems. Bigtech firms operate on the DNA (Data-Network-Activity) framework (Gambacorta et al., 2020), endowing them with a considerable competitive edge through control over extensive alternative data sets. Thus, bigtechs have both experienced developers and extensive data, which can be used in assessing customer creditworthiness. Collaboration with fintechs and bigtechs enables banks to expedite the implementation of ML algorithms in their processes, albeit at the cost of heightened dependency risks and increased external dependencies. Indeed, there is also a hybrid approach when the initial external collaboration evolves to develop internal capabilities, ensuring the bank has sufficient skills for future advancements.

**Table 1.**Summary of the ML application in customer creditworthiness assessment (by authors)

| Deployment approaches | Advantages | Emerging risks | Risk mitigation suggestions |
|---|---|---|---|
| Through internal capabilities | More accurate prediction of customer creditworthiness | Compliance risks and ethical challenges in processing alternative big data | Obtaining customer consent to process their data and data anonymization techniques, ensuring adherence to ethical and legal norms |
| Through partnership (with fintechs, bigtechs) | Financial inclusion | "Black Box" algorithms, also potentially with discriminative criteria | To improve staff and regulators' technical skills |
| Hybrid approach | | | Exclude non-ethical discriminative criteria (gender, race, etc.) |

### 3.2. Advantages

The main advantages that banks gain by incorporating ML systems in creditworthiness assessment are two-fold. Firstly, improved models of creditworthiness assessment lead to better outcomes and contribute to financial inclusion, hence increasing loan volumes. Enhanced accuracy in creditworthiness assessments may aid banks in diminishing the frequency of problematic loans (non-performing loans) and, by reducing anticipated credit losses, amplify the bank's net profitability. Secondly, the currently "unbanked" population can access credit under favorable conditions, which was not possible previously due to the absence of traditional data. This is important both for banks, which can expand their credit portfolios by attracting a new client segment, and for the country in ensuring higher welfare.

The mentioned enhanced accuracy is due to both the more advanced algorithms and also the big data. One of the biggest advantages of ML models is that they can assimilate big data through different algorithms capturing also non-linear connections. Surprisingly, even though more complex algorithms may add to the overall effectiveness of the model, we can record a significant increase in model effectiveness simply by adding more data. It is observed in many studies and it is visually presented in figure 1.

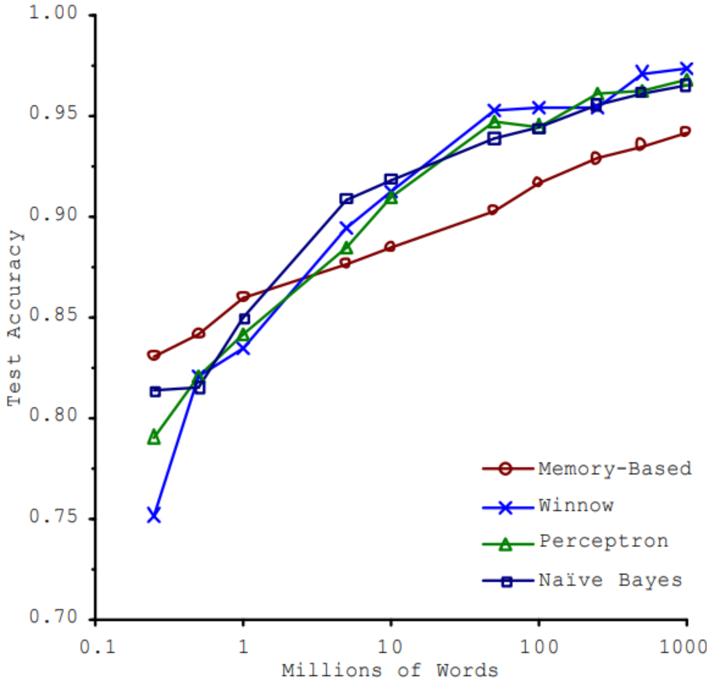


**Figure 1**. The importance of data versus algorithms (Banko & Brill, 2001)

Thus, if there is a trade-off between finding the "best" algorithm and finding new big datasets, it may be beneficial to consider increasing the datasets with new alternative data.

### 3.3. Emerging risks

On the other hand, ML systems used in credit scoring bring new challenges. These are related to the data used in these systems as well as the decision-making algorithms that process the data. It's important to note that the advantage of ML systems becomes evident only when dealing with big data, as they tend to return results with nearly the same effectiveness as models existing in traditional data settings.

However, alternative data for credit scoring typically comes from different companies, such as big tech, telecommunication firms, or other large commercial entities (e.g., online stores). Consequently, compliance with data protection laws in the relevant jurisdiction is essential to avoid big penalties. For instance, within the European Union, the violation of the General Data Protection Regulation (GDPR) potentially brings fines surpassing 0.5 billion euros (GDPR Enforcement Tracker, n.d.). Common GDPR violations relate to processing customer data without adhering to legal standards and data protection. Moreover, companies may need to seek an individual's consent to process their data. Nevertheless, the ethical standards and legal authorizations required for the analysis of individuals' data for such objectives are subject to considerable debate. Notably, one of the main reasons for mortgage defaults is divorce, which could potentially be predicted using data from dating websites (Sadok et al., 2022). However, the ethical norms and legal permission for analyzing individuals' data for such purposes remain highly contentious.

In addition, resulting decision-making ML algorithms can also pose some problems. While these algorithms evolve and improve over time with new big data, there is a non-negligible risk that they may sometimes lead to biased rules for loan issuance based on gender, race, or other criteria. These biases are often due to limited data on certain minority groups, leading to less justified outcomes in creditworthiness assessments. Such biases can contravene the regulatory frameworks of a country and lead to potential prohibitions by regulatory bodies. Even if certain data is readily accessible, it should not be indiscriminately incorporated into ML models, as this can maintain the "black box" nature of these models, making the regulatory bodies more suspicious of fraud and ethical issues. Recently, in the scope of risk management, the National Bank of the Netherlands (DNB) challenged the use of ML in anti-money laundering (AML) combat for the "bunq" online bank. Although the legal dispute did not conclude entirely in favor of the challenger bank (the ML algorithm had difficulties with specific cases), the court affirmed that there was no fundamental reason preventing banks from using artificial intelligence in their AML processes (Monroe, 2022). This was a significant victory for the adoption of innovative solutions and indicates that future implementation of such technologies will likely face reduced pressures from regulatory authorities.

### 3.4. Risk mitigation suggestions

Firstly, when employing big alternative data, it is advisable, when possible, to anonymize these data (Sadok et al., 2022). The development of technologies that anonymize data for subsequent use (for example, customer data from telecommunications companies used in credit scoring) is progressing. However, these techniques have their limitations, and it may not always be feasible to anonymize the necessary data for the desired outcomes fully. Regarding the ethical and legal standards of data usage, banks should test and ensure not only the higher accuracy of these ML systems before their real-world application but also compliance with legal and ethical norms.

Beyond adhering to the rules of data usage, it is also essential to ensure the transparency and comprehensiveness of the outcomes generated algorithms. For this purpose, it is recommended that the staff developing and updating ML algorithms, as well as regulators, possess certain programming skills to avoid treating these algorithms as "black boxes". Additionally, to exclude discriminatory metrics in credit scoring, it is suggested that these parameters should not be used in model development or should not be used when assessing the creditworthiness of a client.

The aforementioned measures will help reduce the challenges associated with ML systems in credit scoring and enhance their comparative advantages over existing models.

While academic literature primarily focuses on the opportunities and effectiveness of ML deployment in banking, there is a notable gap in exploring the actual integration processes within banks. This study focuses on cataloging inherent risks of ML application in creditworthiness assessment models. Further research dedicated to these deployment approaches could significantly enhance the understanding of risk management frameworks in ML applications. The literature consistently highlights the efficacy of combining ML techniques with big data in assessing customer creditworthiness. Some works emphasize its important role in the promotion of financial inclusion. Concerning emerging risks, several studies and practical cases point to the "black box" nature of ML algorithms and accompanying legal and ethical challenges, even though these may not be widely prevalent currently. Our study delineates various risk mitigation strategies, supported by findings in the literature. We suggest that in order to properly evaluate the reasonableness of implementing ML in creditworthiness assessment, banks would need to gauge the advantages against the residual risks of implementation for their own case. To do so, they will need to obtain experts at least in three directions. First, a legal expert that would ensure legal compliance of alternative big data usage, second, credit risk experts with technical skills to interpret the ML algorithms at an acceptable level (i.e., in front of the regulator or the bank's management) and, finally, a CSR (corporate social responsibility) expert that would ensure the compliance with the ethical norms. Ensuring compliance should be understood as broadly compliant with acceptable level of possible impact, for example, the CSR expert has done local research predicting what would be the probable loss in case of materialization of the ethical risks.

## 4. CONCLUSION

To address the key question of the study, the study formulated a summary detailing the crucial aspects of ML in creditworthiness assessment models. The first column includes varying ML deployment approaches in banking models, which, although not the focal point of this research, are deemed influential on the complexity of emerging issues and potential solutions. The second column represents the advantages of the usage of ML techniques highlighting ML applications' ability to enhance customer creditworthiness prediction accuracy when combined with big alternative data. In addition, ML techniques help to decrease the information asymmetry currently present in loan issuance and promote financial inclusion for both individuals and SMEs. The third column represents the main risks that may arise when switching to ML techniques, and it includes, on the one side, compliance risks linked to alternative data usage, as it may be non-ethical or illegal, and on the other hand, the resulting final algorithms, which may seem to be "black boxes" compared to the traditional models. The study combines the risk mitigation actions from both international cases and academic literature. It states that actions are required not only from the banks but also from its jurisdiction's banking regulators and supervisors. The actions include firstly finding acceptable means to use the customer data in ML models through either anonymization techniques or by receiving data usage consent from customers. Secondly, bankers and regulators should train to get more technical skills to understand better the ultimate ML algorithms that would select creditworthy customers. In third place, banks would rather remove the non-ethical discriminative criteria from their model to escape from reputational and legal repercussions.

The findings of the study will help banks to evaluate the overall impact when applying ML models in creditworthiness assessment. However, the study acknowledges three primary limitations: it does not explore variations in ML application issues across different deployment strategies, it overlooks technical complications inherent in ML implementation for credit risk assessment, and it has yet to examine the impact of ML applications on macro-financial linkages, particularly concerning new lending opportunities. Due to these limitations, the study results may not be comprehensive and would require further research to complete the results.

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