How Far Has Our MSMEs Credit Underwriting Assessment in Indonesian Commercial Banks Progressed?

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ARTICLE INFO
ISSN: 2723-1097
Keywords: Micro Small Medium Enterprises (MSMEs); 5Cs of Credit; Credit Underwriting Assessment; Credit Scoring; AI in Banking

ABSTRACT
There is a vast literature on credit underwriting assessment, but many are designed for consumer banking. Given that most banks in Indonesia get their revenue from commercial banking activities, it is critical to recall the main characteristics of current practice as recorded in published papers with cases in Indonesia’s MSMEs credit underwriting risk assessment. This study, in form of semi-systematic review, discusses the industry standard of loan origination framework and the emerging trend of statistical and advanced analytic methods along with their challenges; and focusing on papers on credit underwriting risk assessment with MSMEs datasets leaning on Indonesian data whenever available. Examples given in this paper may indicate the methods used by Indonesian banks to assess the creditworthiness of MSMEs, although there is no clue if either the mentioned studies are implemented in the respective banks or just for academic purposes.

Introduction
As many research findings said, it is generally accepted that Micro, Small & Medium Enterprises (MSMEs) are vital to a country’s economic development. In line with that, the presence and growth of MSMEs in Indonesia (businesses with turnover up to Rp 50 billion p.a. as defined by Government of the Republic of Indonesia Regulation No. 7 of 2021 and as mandated by Law of the Republic of Indonesia No. 11 of 2020 on Job Creation) are proven to reduce poverty when there is some increase in the number of labor absorption (Nursini, 2020) as MSMEs absorb more than 90% of the workforce in Indonesia (Pramono et al., 2021). This essential role places the MSMEs as a powertrain of socioeconomic development and the leading actor in achieving numerous long-term sustainable development goals (SDG) (Šebestová & Sroka, 2020). Although MSMEs have a substantial economic and social impact, they often have poor financial information quality, which causes limited access to banking facilities (Adhityo Dinutistomo & Wibisono Lubis, 2021). Lack of assets as collateral also limits their access to financing from the Bank (Aryani et al., 2020). They relied on personal savings for initial capital and have an ultra-tight product specialization to stay in the market (Syapsan, 2019). Moreover, the challenge in financing MSMEs is the cost of financing remains constant regardless of loan size, as also seen in Indonesia (Wulandari & Kassim, 2016) since the process is labor-intensive and time-consuming (C. Wu & Wang, 2000).
The credit assessment minimizes the information gap between the lender and borrower constructively by evaluating the ability and willingness of prospective debtors to repay and identifies their possibility of conducting fraud (Ashofteh & Bravo, 2021), as well as the loan amount, interest rate charge, and terms (Han et al., 2020). By avoiding bad credit disbursement, the goal is to keep the bank's business as efficient as possible while still ensuring business continuity (Spuchťáková et al., 2015). In Indonesia, this is also obliged by Law of the Republic of Indonesia No. 7 of 1992 regarding Banking, as lastly amended by Law of the Republic of Indonesia No. 10 of 1998 (Banking Law) as the implementation of prudence principle in commercial banks (Disemadi, 2019).

This study will focus on the credit underwriting assessment frameworks and methods, which were introduced in the 1940s and have evolved significantly over the years (Silva et al., 2019). As a quantitative interpretation of the credit assessment, the credit scoring method later became an obligation for commercial banks under Basel Accords. Since then, the usage of credit scoring is not limited to credit-granting decisions but is also applicable to risk management (Louzada et al., 2016). The risk management principles set by the Basel Committee on Bank Supervision (BCBS) are later mandated in the Financial Services Authority of Indonesia's Regulation No. 18/Pojk.03/2016 concerning Implementation of Risk Management for Commercial Banks.

There is a vast literature on credit underwriting assessment and impossible to index all published work (Breeden, 2020), but many of them are designed for consumer banking. Considering that the majority of banks in Indonesia got most of their revenue from commercial banking activities, hence it is essential to recall the main characteristics of the current practice in order to synthesize on the state of knowledge of credit assessment in MSMEs financing; enriched with some published papers with cases in Indonesia and as well as some of the possible advancement of methodologies in this topic. This paper is also intended to increase the overall quality of research in this field, as it aims to identifying and bridge the knowledge gaps within conventional practice, credit assessment automation, and the possible use of advanced analytics methods such as machine learning and its challenges as well as opening research questions in this topic.

Nowadays, digital-oriented transformation in every single industry is inevitable, and the use of machine learning in banking is the recent hot topic in its industry since numerous recent research have discovered compelling evidence that without relying on restricted assumptions, machine learning methods may significantly increase the performance of the model compared to the standard statistical methods (N. Chen et al., 2016). The focus of the possible credit assessment advancement writing will be on which areas and how the use of artificial intelligence can be possibly applied to enrich around generally accepted MSMEs credit assessment systems instead of listing.
lengthy equations of each algorithm to use or comparing model performances between algorithms as they are continuing to develop rapidly.

Method

Credit underwriting assessment is a part of the four-eyes principle in banking practice (Nurwahjuni & Shomad, 2017). Banks' practices may differ each other because it is the bank's internal policy to assess, risk map, and decide whether to grant credit to a debtor or decline the prospective debtor's loan application based on their risk appetite. This may be influenced by the bank's business strategy as well. Therefore, this paper will cover the main elements that most large banks in Indonesia commonly use.

The method used on this paper is semi-systematic review, as discussed by Snyder (2019). Which has the main point to identify all potentially relevant research for the studied topic, and to synthesize how this topic has progressed over time. All sources of scholarly relevant literature on this study are taken from published research articles in English, while some are in Bahasa Indonesia, and no banks' unpublished internal information will be mentioned here in this study.

Literature Review

This section comprises three subsections. We discuss universally accepted credit underwriting risk assessment in Indonesia, followed by the use of statistical model in second subsection. The final subsection discusses advancement in creating models.

Conventional Credit Risk Assessment for MSMEs in Indonesia

Some steps are universally applicable in the commercial bank's credit origination process, ranging from evaluating applications, calculating the credit rating, determining risk-adjusted pricing, and collateral valuation (Witzany, 2017). These activities, in the majority, are covered in the classic credit rationing of credit analysis, firstly known as the three Cs but evolved as the five Cs framework. The five Cs are capacity, character, capital, collateral, and conditions. By its nature of assessment, three of the five Cs that constitute the basis for quantitative analysis are capacity, capital, and collateral, whereas character and some parts of the conditions are subjective-qualitative interpretations (Baiden, 2011). These criteria of 5Cs fulfil the approach to determining the customer's ability and willingness to repay (Chi & Meng, 2019), even though there is no formal definition of each criterion.

The 5Cs framework is the most common assessment in Indonesia and has become the main requirement for MSMEs to get financing (Fatira AK et al., 2021) from commercial banks and other lending institutions such as microfinance, as shown in some nationally published papers by Indonesian scholars. Most of them studied about five Cs implementation and suggestions in the bank's local branch to suppress non-
performing loans. Although the 5Cs are still the industry standard for loan approval in Indonesia, in previous studies, the findings of empirical studies in individual (each criterion) 5Cs regression analyses did not have a consistent result on its effect on non-performing loans (Sakti & Anisykurlillah, 2017), which is understandable as expected behavior from linear regression models. In the same study, despite their dataset being in a cooperative body in Indonesia, it is known that they (with two other parameters) simultaneously affect the non-performing loans. There is no evidence or literature associated with the dataset in Indonesian commercial banks for that topic.

The first of the 5Cs is capacity, which aims to assess the repayment ability of the prospective debtor to operate its business and seek profit (Suratini & Parera, 2020) by measuring revenue and compared with recurring debts (Sisilia et al., 2015) to avoid default risk (Vidya, 2018). It is also common to assess key financial ratios from the (in MSMEs cases mainly using pro-forma financial statement) income statement given by the applicant to the bank. The bank also usually conducts surveys to look closely at the current and prospects of the business (Sylvana, 2021). This includes the due diligence of the core business products, its marketing roadmap, and challenges to selling the products (Monulandi et al., 2016). Additionally, the bank will look at the management's profile and its employees' ability to run the business successfully.

Character assessment was conducted by conducting interviews and data verification of prospective debtors to weigh their creditworthiness and predict their willingness to repay (Tektona & Risma, 2020). The lender side also will assess their integrity, stability, and honesty (Beaulieu, 1996) to prevent fraudulence attempts. This character judgment is sometimes also influenced by the prospective debtor's socio-cultural background (Pasaribu et al., 2019). To assess more of the character criterion, in micro-businesses that still mix the owner and business cash flow, the owner's credit records, such as a mortgage, vehicle financing, and credit cards owned, are also used in addition to the business' credit record to assess the application. The requirement of a credit record sometimes leaves out people with little to no credit history (Lee, 2019).

Capital is also an important part, as investment or working capital financing cannot rely only on debt financing, and it substantially impacts the likelihood of MSME credit approval (Siswanto et al., 2019). The bank will assess key financial ratios from the (in MSMEs cases primarily using pro-forma financial statement) balance sheet of the firm and keep the given total limit of credit to equity ratio under the bank’s risk appetite. Capital also indicates how much money is at risk if the business fails (Wasiuzzaman et al., 2019). Under this category, the bank will assess if the credit application is at an acceptable amount and not over-financing the debtor as well.

Except for a couple of categories in the government micro-lending program, collateral is required for most banks' facilities for MSMEs. Providing assets as collateral to the bank might be a strategy for prospective debtors to lower informational

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asymmetries in the credit-rationing problem (Steijvers & Voordeckers, 2009). The longer the credit maturity period, which means the riskier the credit, the collateral will give confidence to the bank to approve credit applications (Sari et al., 2020). A study by Prihantoro & Nuryakin (2020) found that collateral as a requirement for receiving a loan statistically positive contributes to the bad credit-disbursement reduction in Indonesia. Therefore, it is not surprising that a study by Marta & Satria (2015) shows that collateral plays an important factor in credit decisions. Banks in Indonesia accept both liquid (e.g., cash) and illiquid (e.g., real estate) as collateral for secured loans. The current value of solid collateral will be determined with an independent external/third-party appraisal and locked under a legal agreement scheme.

The last one is Conditions. Although this "condition" is defined as "the condition of the economy," two paradigms divided the definition. The first one is assessing the entity’s/internal condition, as can be found in Simatupang et al. (2021) and Amelia & Marlius (2018). The others are assessing economic conditions associated with the prospective debtor's business (Fernando & Siagian, 2021). However, in practice, it can either only assess the condition of the external factors that have an impact on the business, such as recession, industry issues, business cycle (Guiral, 2012), and even political and surrounding social conditions (Safa’atillah, 2020) or doing both internal and external assessment (Baskara et al., 2016). The primary goal of this assessment category is to learn about the current business environment and its prospects.

The application questions in Indonesian commercial banks' assessment for MSMEs using the 5Cs framework can be seen in table 1, and this may not be the exact case on what was implemented in real-world use.

Table 1. Typical Credit Assessment Questions

<table>
<thead>
<tr>
<th>Aspect</th>
<th>Typical questions for assessment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Character</td>
<td>1. How cooperative is the debtor?</td>
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<td></td>
<td>2. Is the prospective debtor ever failed to meet the debt payment?</td>
</tr>
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<td></td>
<td>3. Is the prospective debtor holds a good reputation?</td>
</tr>
<tr>
<td>Capacity</td>
<td>1. How long is the key persons' business experience?</td>
</tr>
<tr>
<td></td>
<td>2. Do they manage a good relationship with customers and suppliers?</td>
</tr>
<tr>
<td></td>
<td>3. What is the unique selling proposition of the business?</td>
</tr>
<tr>
<td></td>
<td>4. What is the key revenue stream for the business?</td>
</tr>
<tr>
<td>Capital</td>
<td>1. Are there any other loans outstanding for the business?</td>
</tr>
<tr>
<td></td>
<td>2. How is the key financial ratio compared to other similar businesses?</td>
</tr>
<tr>
<td></td>
<td>3. What is the purpose of the loan?</td>
</tr>
<tr>
<td>Collateral</td>
<td>1. What collateral could be offered to back the loan?</td>
</tr>
<tr>
<td></td>
<td>2. Is the collateral clear from any disputes?</td>
</tr>
<tr>
<td></td>
<td>3. How marketable is the collateral?</td>
</tr>
</tbody>
</table>
### Aspect | Typical questions for assessment
---|---
Condition | 1. How sensitive is the business with commodities/currency prices?  
2. What is the trend of their industry sector for the period of the loan?  
3. What local/national regulation could affect the business?

Source: processed from literatures.

Aside from that mentioned above, although not a typical use, a study by (Ismawanto & Finanto, 2019) added the Constraints as the sixth component of the "five Cs" framework from their study in a commercial bank in Indonesia. The reason behind this is they argued that Constraints are social-psychological barriers or obstacles that exist in a specific area or community, making it difficult to do a project/business. Other alternative frameworks are also used depending on the bank's internal policy and mostly can be found in State-Owned Enterprise Banks. Two of the most popular frameworks are 7Ps: (good) Personality, (rating of) Party, (loan) Purpose, (company’s) Prospect, (ability to re-) Payment, (company’s) Profitability, and (credit) Protection (Hapsila & Astarina, 2020) and 3Rs: Returns, Repayment capacity, dan Risk bearing ability (Cahyadi & Windirah, 2021) but they are never used in isolation and are always used in conjunction with the 5Cs framework.

Although the five Cs of credit framework is the industry standard for credit-granting activities, there are still some flaws in this framework that have become a classic problem for credit assessment. Learning from the studies in another country, which may also be happening in Indonesia and could be empirically assessed for future studies, the challenges of its implementation are the quality of data because of credit officer error, inconsistency in credit policy application across decision-makers, high costs of labor and work to assess, and insufficient acquired data from the prospective debtors (Capon, 1982). The majority of the inconsistency comes from the qualitative factors that are hard to assess and creating a bias in credit assessment for years. In Indonesian cases, there is a case in a non-bank lending institution, as can be found in Mashudi et al. (2018), and counterproductive work behavior in assessing credit application with the five Cs framework by lending officers in an undisclosed bank as can be found in Sawitri et al. (2021).

**Statistical Methods Use in Credit Risk Assessment in Indonesia**

The possibility of poor subjective judgment of the five Cs framework leaves a significant gap in credit assessment. This problem causes inefficiency in the bank's business because the variance of decisions among credit decision-makers is high, resulting in credit disbursement that is not in accordance with the firm's risk appetite. As a result, attempts are being made to quantify all of the assessment points in order...
to solve these issues and use empirical statistical evidence to formulate the optimal policy based on the bank's willingness to take risks from credit disbursement.

The widespread use of the FICO scoring system from The Fair Isaac Companies in the United States, which uses techniques for treating the credit assessment problem probabilistically, revolutionized the game of credit scoring. Like other historical statistical movements, it developed in the hands of practitioners working in the field with domain experience rather than being developed and disseminated by academic or professional statisticians (Poon, 2007). FICO's credit scoring was initially intended for consumer credit, but the method has evolved and adapted over time for assessing SMEs' loan applications and other credit assessment issues.

Simple credit scoring was evaluated by assigning prescribed points from the scorecard to each application question (may derive from the five Cs framework) and summing all weighted points to arrive at the total score. Some banks in Indonesia also set different points earned for the same question/category on the scorecard based on the debtor's industry classification (Aripradita & Wiryono, 2012). A higher score might indicate greater creditworthiness or vice versa. The total score generated is later used to determine whether or not someone is creditworthy in accordance with the bank's policy. The application will be denied if the total score falls below the threshold and assumes no other factors intervene. In addition, automatic knockout criteria may also be applied for unacceptable reasons according to the bank's policy (e.g., bad collectability record).

Based on the historical data in a certain period of time, the cut-off score is evaluated by calculating and analyzing a large volume of data to discriminate between good credit and bad credit disbursement (Khemais et al., 2016). Different cut-off points may also be set for more than two categories as believed that the use of multiple categories could provide more insight into risk management (W. Chen et al., 2012). Logistic regression is one of the internationally famous classical methods alongside discriminant analysis and their respective variations (such as Altman (1968) Z-score model) to create the cut-off policy based on data (Ince & Aktan, 2009). The cut-off value, or the credit rule, is the tradeoff decision by the bank between accepting more good credit misclassified as bad credit or more accepting bad credit misclassified as good credit based on statistical modeling.

In Indonesian scholars' studies, some of the mentioned statistical methods for banks' credit assessment in the MSMEs context are using the multiple regression analysis, Bayesian multivariate probit model, Bayesian multinomial logit model, and Simple Additive Weighting (SAW) to discriminate between good and bad borrowers or predicting the applicant's probability of default. For example, Hermanto & Gunawidjaja (2010) tried to find optimal logit and probit models on 1,845 Indonesian SMEs (with annual sales less than USD 5 million) between 2005 and 2007 from ABC
(disguised) Bank, one of the five largest banks in Indonesia data with 345 of them are in the default state. Based on their logistic regression and probit modeling using the key financial indicators as model input, the current ratio and interest coverage ratio have negative relationships; and the firm's average collection period has a positive relationship with its probability of default.

Another study by Setiyawan & Frieyadie (2020) assesses the credit application for the microcredit government program with 30 debtors in Bank Mandiri KCP Dramaga using Simple Additive Weighting (SAW) with weighting value into fuzzy numbers based on the 5Cs framework to rank the debtors by its creditworthiness. Lesser sample can be seen in Rekawati et al. (2019) with ten prospective microcredit debtors in Bank Mandiri KCP Gedung Pusat Kehutanan. In addition, Pramudita, (2021) tried using Altman's revised Z-score and Ohlson's O-Score to predict bankruptcy in Bank Mandiri's Small-Medium Enterprise debtors with unknown data sizes. Hamzani & Achmad (2018) assessed 20 government microcredit program (KUR/Kredit Usaha Rakyat) applicants using Altman Z-score and Ohlson's O-Score in a specific region (Pontianak). The study from Halim & Humira (2014) created a scorecard based on logit and probit regressions for a bank in Indonesia using three groups of risk factors (quality of management, business risk, and financial risk) from 3,848 firms, with 110 of them defaulting. The GINI Coefficient and Kolmogorov-Smirnov (KS) scores were calculated to validate the model and measure the efficiency of the scorecard.

The use of the statistical method directly answers the challenges of the conventional/personal judgment-based credit assessment method. By quantifying all of the scoring factors and learning from historical data or expert judgment, it helps the banks standardize the rules among the decision-makers with the statistical model. Therefore, the chance of getting a high variance on bad credit disbursement can be suppressed and under the control of the bank's risk appetite. However, the statistical modeling must be at a representative number of samples to get a model near the population, which sometimes takes time and cost. The statistical modeling relies on assumptions, cannot deal effectively with high-dimensional data, and has costly computation time (Wang & Zhang, 2020). This has been a classical statistical method challenge since credit scoring was first used for assessing MSMEs credit applications as the debtor's condition, credit facilities, and loan purpose are more heterogeneous than consumer credit or mortgage (Mester, 1997).

Credit risk assessment for SME loan applications is managed almost entirely by automated credit scoring systems in mature economies (Calabrese et al., 2019). The advancement of computing power and ICT positively impacts and optimizes the bank's business processes. It helps handle a large volume of applications, reduces processing time and effort costs, and enhances the customer experience (Nath et al., 2020). This also allows the bank to go a step further in standardizing risk appetite across their organization, as loan processing in one location/branch will be treated at
the same standard as loan processing in other locations/branches. Major Indonesian banks have implemented a standardized platform for MSMEs loan processing and scoring, and some of them provide integrated processes from application submission to credit disbursement. To name a few of the platforms in Indonesia's most prominent banks: SME Scoring System (SMESS) in BMRI (Ningsih & Budiwati, 2020), Loan Approval System (LAS) in BBRI (Febrianti, 2022), Integrated Credit Origination System (ICOS) in BBCA (Farina & Winta, 2020), and Electronic Loan Origination (eLO) in BBNI (Aprianto & Achjari, 2011).

Credit Scoring Agency, in addition to the bank's internal credit scoring, is also expected to play a role in SME financing in Indonesia. IdScore+ (idscore.id) by PEFINDO Biro Kredit as one of the Private Credit Bureau (PCB) recently began providing credit scoring services for small businesses aside from consumer credit. Apart from the five Cs assessment, this rating is based on both financial and alternative data approaches to provide an opinion for the bank's credit assessment, complete with the debtor's probability of default. With its ability to evaluate alternative data from other data providers, it aims to help the underserved and underbanked gain access to financing. As Rahardyan (2020) reported, some banks and other financial institutions, such as fintech lending, have used this product and method as part of their credit assessment.

**Studies and the implementation of advanced analytics in Indonesian credit risk assessment**

Advancements in computing power have made advanced analytical methods more viable and affordable to research and implement over the last few decades. Numerous emerging algorithms are now available to learn, interpret, and predict from data. Even more, the model could be optimized to achieve better performance by conducting experiments, evaluating machine learning algorithms, and tuning parameters.

This massive growth has also affected the financial services industry, as the remainder of this section will explain some of the concepts and use cases. In the context of credit assessment, it aids in overcoming some limitations of simple statistical methods and is much anticipated to increase underbanked access to credit, lower the cost of doing business, minimize credit losses, and reach efficiencies.

As raw data are not always available as desired, preparing the data to be usable is vital as a part of the advanced analytic process. The treatment available includes decreasing or increasing feature vectors’ dimensionality and/or selecting the right amount of statistically significant features (Zheng & Casari, 2018) other than adding/removing, correcting the variables/features, and standardizing the data. Using one or more of these methods is an attempt to optimize the whole model/prediction and reduce the model's over-fitting to perform well for the task.
For instance, resampling and oversampling could be used to optimally predict each class in credit scoring with imbalanced data problems (Irawan & Samopa, 2019) in addition to the under-sampling method. Another example of a method that can be used for credit evaluation is data augmentation implemented on a continuous dataset to forecast financial data (Fons et al., 2020). Lokanan et al. (2019) observed that the result of fine-tunings for financial index missing data would differ when a missing value is replaced with a value from the standard normal distribution. That could be an alternative to removing the data from the computation.

In reducing dimensionality, Yoshino & Taghizadeh-Hesary (2015) used Principal Component Analysis (PCA) and hierarchical clustering to determine the minimum number of components that can account for the correlated variance among SMEs and how much each individual SME is similar to others based on financial statements. Initially, 11 financial variables of 1,363 SMEs from Asian bank customers were evaluated, and the findings revealed that four variables (net income, short-term assets, liquidity, and capital) are significant for describing the general characteristics of SMEs for the case.

With the use case described beforehand, PCA is one of the unsupervised methods in advanced analytics. The unsupervised methods required none of the need for human intervention to uncover hidden patterns or cluster unlabelled datasets. These hidden patterns, or clusters, are beneficial to improving the performance of credit rating classification problems. It can be helpful to refine credit policy for a better credit portfolio quality as well.

Another example, as studied by Ahelegbey & Giudici (2022), uses 15,045 small-medium enterprises in Southern Europe's peer-to-peer lending dataset, with 1,632 defaulted and 13,413 non-defaulted companies. They used k-means clustering with k = 2, which allows segmenting of a heterogeneous population into clusters with more homogeneous characteristics. As a result, the clustered sample outperforms the population's predictive performance gain. This advantage can be increased further by considering the observed default percentage cut-offs, which differ between the two clustered samples.

Because this credit scoring problem distinguishes between good and potentially bad debtors, classification methods are widely used in the AI field, whether they are divided into two or multiple classes, as implemented for statistical use in building credit scorecards. Supervised learning techniques with discriminative models are most commonly used in this artificial intelligence process to build credit scoring models under the machine learning subcategory. This makes the use case not only relies on internal labeling but also enables the implementation of shadow rating, such as studied by Balakrishnan & Thiagarajan (2021).
As for implementation, the expert system is the most straightforward use case of artificial intelligence and the widely-known cut-off and classification method. This non-parametric technique uses professional judgment (represented as a set of rules) to set the cut-off value and explains why it was rejected (Kritzinger & Van Vuuren, 2018). A hybrid model based on expert judgment and modeling is also typically used to answer the need for understanding current business practices (non-financial factors) as well as the quantitative factors of the debtors Do et al. (2019).

Many supervised algorithms are available to build a model. Some are from the classification and regression branches, such as popular Decision Trees, k-Nearest Neighbor (KNN), and Support Vector Machine (SVM). Deep learning methods such as Neural Networks are available as well. Even reinforcement learning to optimize the acceptance score threshold can be seen in (Herasymovych et al., 2019). All come with the algorithm's unique behavior and broad advancement over time. The model is chosen by determining whether the model's underlying theory and assumptions are justifiable. In addition, aside from just using a single algorithm, ensemble learning builds a typical predictive model by combining multiple algorithms to improve prediction performance (Rokach, 2010). The ensemble's overall prediction will likely be better than a single algorithm as the pairing algorithm tends to compensate for the errors (Sagi & Rokach, 2018).

Each algorithm has hyperparameters that control the behaviors of training algorithms and highly affect the predictor's performance (J. Wu et al., 2019) aside from the data itself to get the optimal prediction. This configuration phase demands expert experience, and as trial-error search is time-consuming, hyperparameter tuning would be a computationally expensive process (Yang & Shami, 2020). Therefore, there are attempts to avoid those problems by using automatic hyperparameter optimization (HPO) such as grid or random search to more advanced techniques like evolution strategies, Bayesian optimization, and Hyperband (Bischl et al., 2021).

Advanced analytics also enables building a model from an existing model, as known as transfer learning, which could improve model accuracy and allow whoever with low data availability to reuse or transfer information from previously learned tasks. For example, a study by Suryanto et al. (2022) used the data from peer-to-peer lending (Lending Club datasets) to predict the probability of default of small businesses from a debt consolidation model. They used the Progressive Shifted Contributions method to varying network architecture and hyperparameters to find the best balance of learning from source and target domains and investigate how and why transfer learning improves model accuracy using Shapley Additive exPlanations values.

In Indonesia, some use of machine learning in credit scoring for productive loans is recorded in some papers, such as those studied by Ikasari & Hadzic (2013). They used
96 credit applications (ranging from IDR 1M up to IDR 50M) with 38 non-performing loans at the time of collection from a bank. With the help of the Decision Tree algorithm, they gained 94.34% accuracy evaluated using 10-fold cross-validation aside from using the Apriori algorithm in the data mining case. Pratiwi et al. (2019) use KNN and Pseudo Nearest Neighbor to classify 265 debtors in Bank X of Wonogiri Regency, Central Java, for the Government Microcredit program. With the APER value, they gained 98.11% accuracy for the k-NN method with k = 1 and 79.25% for the PNN method with k = 13. Another implementation studied by Afrilia et al., (2021) uses Multivariate Adaptive Regression Spline (MARS) algorithm using 3,309 debtor profiles with 235 defaulting from a regional bank in West Java. They gained 0.00% type I error and 0.54% type II error from five significant variables (age, living cost per income, home ownership status, permit and impact aspects, business sector, and duration of business).

Not only just for classifying the potential default of prospective debtors but driven by its use cases, there are also many alternatives for employing advanced analytics as complementary predictors in credit origination assessment. The use of complementary predictors in the advanced analytics era could be influential in enriching generally accepted MSMEs credit assessment systems. As an example, Sopian et al., (2019) use an artificial neural network (ANN) and support vector machine (SVM) to predict approved working capital loan value in Indonesia and validate the model with 10-fold cross-validation. Another implementation was studied by Rizki et al. (2017), as they used machine learning to detect firms that issued fraudulent financial statements (FFS) from 124 companies and 24 of them conducted financial statements fraud as signified with ANN and SVM from 9 statistically significant variables. This work was later retested by Hidayattullah et al. (2020) with Back Propagation Neural Networks and Support Vector Machines algorithm to gain better modeling results.

These implementations are not limited to the ones listed above, and we can imagine how massive the opportunities to employ advanced analytics to support the main credit scoring system are. Some unexplored topics such as utilizing machine learning to conduct invoice-based financing, objectively charge the interest rate, see behavioral patterns of the prospective debtor (SME owner) ’s non-productive loans (credit card, mortgage, etc.), forecasting business cash flow, and risk-weighting each business sector based on relevant forecasts (commodities price, foreign exchange, consumer confidence index, purchasing managers index, etc.), get a second opinion for the collateral market price, analyze social media data as researched a lot, and many more.

The accuracy metric, which is identical used in the "simple" statistics, is used to evaluate the model generated by the algorithm, primarily in classification problems. Using sensitivity and specificity, as well as other methods such as G-mean, F-measure, and Area Under Receiver Operating Characteristics Curve (AUC), the model's error leads to a bargain. Therefore, the bank’s risk appetite is crucial to the configuration and
application of advanced analytics. Furthermore, it is common to use test data to indicate how the model would predict if it meets new data. There is no prescribed optimal value for train/test splitting the dataset as it relies on the total sample data size. Other popular evaluations for models include leave-one-out cross-validation and k-fold cross-validation; the last mentioned is where a model is trained and evaluated in "k" iterations (Raschka, 2020).

As defined by Basel II as a quantitative comparison of forecasts and actual values, backtesting could also be applied to the advanced analytics model. Grishunin et al., (2021)’s study is one example of evaluating a model as after they categorized 177 SMEs into eight classes based on their one-year probability of default and normalized factors ranging from [0,10], they selected the model specification using the Gini coefficient, accuracy and recall criteria, and Kolmogorov-Smirnov (KS) criterion. The Hosmer-Lemeshow and Spiegelhalter tests were later taken to indicate that there are no statistically significant deviations between the observed and theoretical PDs, indicating the quality of the rating system.

However, the main characteristic of most machine learning algorithms is that they are not straightforwardly interpretable or popularly known as the "black box." This characteristic is not suitable to use in domains requiring a clear and rational justification of individual decisions (Freitas, 2014). Therefore, interpretable machine learning models, such as those explored by Afrilia et al. (2021), used the MARS algorithm to comply with the Financial Services Authority (FSA). Another approach was taken by Bussmann et al. (2021), which used the TreeSHAP post-processing method to gain the determinants of the XGBoost model.

Another issue arising from the use of advanced analytics is data quality, which can cause model risk. Although problems such as unbalanced datasets, redundant data, and a small number of missing values could be solved with pre-processing methods, it is a different story if the data is affected by operational risks, such as an officer inputting incorrect data; as poor data quality leads to overfitting and the risk of biasing the model (Gupta et al., 2022). The overfitting means that the model unable to predict anything useful if inputted by unseen data.

This data quality problem could also bring unfairness and discrimination issues from predictor bias. Although the risks are not as significant as creating a model in consumer credit, there is still a bias if alternative data in MSME credit, such as the owner's school and degree, are included to increase prediction accuracy (Brotcke, 2022) and could impact the bank's reputation. Nevertheless, the risk of unfairness is not just on alternative data but also on "proxy discrimination," in which it appears that there is no discrimination, but there actually is because of the interaction or triangulation of several variables (Prince & Schwarcz, 2020). Personal data protection is also an issue
when alternative approaches such as media social scoring are used as a part of the credit decision.

The regulation in regards of consumer protection for the use of advanced analytics in the banking industry leans on Indonesian FSA regulation no.13/POJK.02/2018 on Digital Financial Innovation in the Financial Services Sector, which refers to OJK Regulation 1/POJK.07/2013 concerning Consumer Protection in Financial Services Sector, which this year updated by 6/POJK.07/2022 on Consumer and Community Protection in Financial Services Sector. It stated that consumer protection should apply the principles of adequate education, openness and transparency, fair treatment and proper business conduct, asset/data secrecy and security, and efficient dispute resolution.

**Conclusion**

The primary goal of this research, which is to recall the overview of the main characteristics of the current practice of MSMEs credit underwriting assessment, with some cases in Indonesia, is presented in the earlier section as reported and studied by some scholars on this particular topic. The examples in this paper may indicate the methods used by Indonesian banks to assess the creditworthiness of MSMEs, although there is no clue if either the mentioned studies are implemented in the respective banks or just for academic purposes as it is one of their own confidential information, which become the limitations for this study.

For short, the 5Cs of credit are still industry standard in assessing a potential MSMEs debtor to lower information gap. This framework is organically growing in the practician, and as a result, there are meaning shifts between them. Notably, the “condition” criterion had two distinct meanings in the published works of literature. The empirical studies of the 5Cs framework are encouraged. One idea is to affirm that each criterion or the whole framework systematically affects non-performing loans in MSMEs credit at commercial banks. Additionally, a minority of banks employ additional frameworks, such as 7Ps and 3Rs, which typically paired with the 5Cs framework.

In terms of the use of statistical and advanced analytics methods, they help to discriminate between potential good and bad debtors based on the bank's historical data. This approach is also valuable for splitting into credit ratings with more than two classes (Internal Ratings-Based Approach/IRBA) which later performed scorecard validation for back testing. Moreover, modeling automates the process and standardizes the rules among the decision-makers which also the case of the use of IT in credit process. Alternative and supporting uses of employment of classical statistics and advanced analytics are also leaving a big question and plenty of interesting use cases to explore.
The main issue of the classical statistics approach is to get the optimal cut-off point(s) under the bank's risk appetite, while most advanced analytics are learning by themselves. There are more concerning issues for advanced analytics, such as the fact that many algorithms are uninterpretable, and there is a lot to investigate on interpretable machine learning in this topic. However, with these more advanced solutions to the classical problem, experts are still needed to interpret the model (Molnar, 2019) and intervene in uncommon and special cases (Liu, 2001). Data availability will be challenging for the academic domain as the law protects the banks' data, and collaborations with practitioners are encouraged to enrich the literature on this field. If possible, it is worth exploring if systematic credit assessment and its advancement could be reflected in the bank's financial statements or credit portfolio quality. A new framework for this problem may be created to better manage the credit underwriting assessment.

Declaration of Interest

The author declares the financial interests/personal relationships, which may be considered potential competing interests as the author has an employment relationship with PT Bank Central Asia Tbk.

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