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Implementing Innovative Credit Scoring (ICS) for Credit Risk Assessment and Loan Origination

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ABSTRACT

This research aims to analyse the implementation of Innovative Credit Scoring (ICS) in the financial industry through case studies of banks and fintech startups. This research uses a qualitative approach with case studies as the primary research design. The results show that ICS can improve process efficiency, scoring accuracy, and inclusiveness of credit access. ICS has significant practical implications, including improved efficiency, more accurate risk assessment, and more inclusive access to credit. Recommendations include cooperation with technology companies, regulatory oversight, attention to ethical aspects and algorithm bias, and developing a validation framework.

Keywords: Innovative Credit Scoring, Credit Risk Assessment, Non-Traditional Data, Process Efficiency, Credit Access Inclusiveness

JEL Classification: G21; G32

1 Introduction

In banking and finance, credit risk assessment and lending decisions are critical steps that affect the stability and sustainability of financial institutions (Gambetta et al., 2021). Statistical data shows an upward trend in the distribution of financing loans for several businesses, including oversized, medium, small, micro, and other categories. This trend indicates that there are bright prospects for the sustainability of financial institutions.

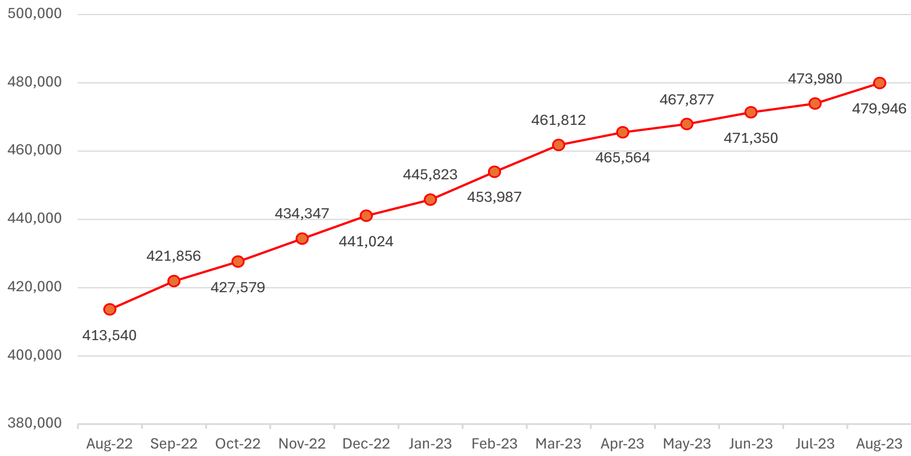

Figure 1. Graph of the upward trend in lending from August 2022 to 2023

Source: OJK, 2023

The credit risk assessment methods traditionally involved analysing financial data and customer information (Mahbobi et al., 2021). However, information technology and data analytics developments have provided new challenges and opportunities in this process. One emerging concept is Innovative Credit Scoring (ICS), which combines technology and advanced analytics to better understand customer credit risk (Wijaya, 2023).

Previous research has explored various applications of technology in credit risk assessment. For instance, Yu et al. (2020) examined the integration of non-traditional data sources, such as user behaviour, digital transactions, and social media data, and found these innovations to enhance the accuracy and efficiency of credit evaluations. Similarly, Tao et al. (2018) highlighted the potential of leveraging such data to develop predictive models for better risk management. Paltrinieri et al. (2019) demonstrated the benefits of advanced analytical techniques, including machine learning, in creating more comprehensive credit risk assessment frameworks. Despite these advancements, certain research gaps persist. First, many existing studies focus on theoretical frameworks and simulations rather than providing practical insights into implementation within real-world financial institutions. For example, Wijaya (2023) noted that while advanced credit scoring models have been proposed, their adoption in operational contexts, particularly in smaller financial institutions or fintech startups, remains limited. Additionally, there is insufficient exploration of the ethical implications and potential biases in algorithms relying on non-traditional data. Research by Tigges et al. (2024) cautioned against the unintended consequences of algorithmic bias, emphasising the importance of ethical safeguards in credit risk assessment. Finally, most existing studies predominantly examine large financial institutions, with limited analysis of the unique challenges and opportunities faced by smaller entities, such as fintech startups, in applying these innovative techniques (Paltrinieri et al., 2019). Addressing these gaps is critical to advancing both the theoretical and practical understanding of Innovative Credit Scoring.

This paper aims to investigate the concept of Innovative Credit Scoring (ICS) as a basis for credit risk assessment and lending decisions. This paper will explain ICS's fundamental principles and advantages in improving credit risk assessment accuracy and operational efficiency within financial institutions. In addition, this paper will also analyse the challenges that may be faced in implementing ICS, such as data security, algorithmic bias, and lack of leading practice standards. In addition, this paper will also explore the opportunities and benefits offered by ICS in the context of credit risk assessment. The paper will focus on ICS's basic concepts and implementation within financial institutions, emphasising credit risk assessment and lending decision-making. Furthermore, the paper will cover the challenges associated with ICS implementation and the opportunities and benefits offered by this approach. However, this paper will not discuss in detail the technical and mathematical aspects of the ICS model but rather will provide an overview that can be understood by readers who have a basic understanding of credit risk.

2 Literature Review

2.1 Basic Concept of Credit Scoring

Credit scoring is a statistical method used to assess the credit risk of a potential borrower (Pang et al., 2021). It utilises historical data and individual characteristics to generate a credit score that reflects the likelihood of timely debt repayment (Trivedi, 2020). Credit scoring allows financial institutions such as banks or other lending institutions to make more informed decisions regarding credit risk assessment, loan approval, and interest rate determination (de Paula et al., 2019). Credit scoring provides several essential benefits in credit risk assessment, including objectivity, efficiency, accuracy, scalability, cost reduction, and risk reduction (Edla et al., 2018). Credit scoring methods use objective criteria and mathematical models, reducing the risk of subjective judgment (Guo et al., 2019). By automating the assessment process, credit scoring can improve the efficiency and speed of lending decisions. Credit scoring provides a more accurate credit risk assessment by combining historical data and careful statistical analysis. Credit scoring can be applied consistently across market segments and many loan applications (Pang et al., 2021). Through improving the accuracy of credit risk assessment, credit scoring can reduce the risk of non-performing loans and the associated costs (Römer & Musshoff, 2018).

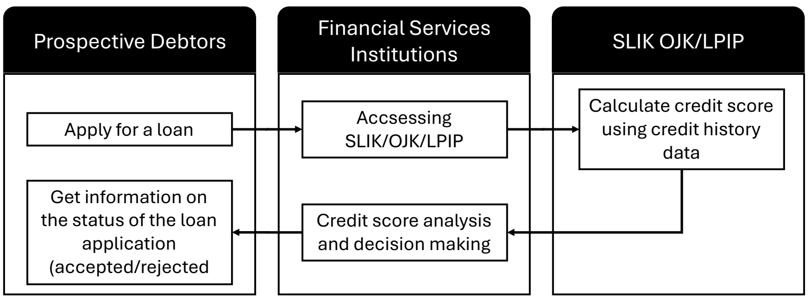

Figure 2. Manual credit scoring scheme

Source: (Katadata, 2023)

2.2 Innovative Credit Scoring (ICS)

Innovative Credit Scoring (ICS) is an approach to credit risk assessment that adopts advanced technology and analytics to collect and analyse more extensive and in-depth data (Edla et al., 2018). ICS uses innovative approaches to collect data, create accurate predictive models, and provide a more complete view of a customer's credit risk (Giudici et al., 2020). The working principle of ICS involves the following steps (Zhang R & Qiu, 2020):

1. Comprehensive data collection: ICS leverages structured and unstructured data resources, including internal financial institution data, data from third parties, transaction data, social data, and digital engagement data.
2. Data preparation and preprocessing: The collected data needs to be prepared and processed for further analysis. This process includes data cleaning, normalisation, removing outliers, and merging different data sources.
3. Analytical modelling: ICS uses analytical techniques such as statistical modelling, machine learning, and artificial intelligence to develop a predictive model. These models will incorporate significant variables to accurately predict credit risk levels.
4. Model validation and evaluation: ICS models must be tested and validated using independent historical data. Model evaluation involves performance metrics such as prediction accuracy, sensitivity, specificity, and area under the curve (AUC).
5. Decision-making: Based on the credit score generated by the ICS model, financial institutions can make more informed decisions regarding the granting of loans, setting interest rates, or rejecting loan applications.

ICS uses various types of data in the credit risk assessment process, including financial, demographic, alternative, digital engagement, and external data (Edla et al., 2018). Personal or business financial data include financial statements, bank accounts, credit card transactions and income information. Data such as age, gender, occupation, education and marital status to understand individual profiles and characteristics. ICS collects and analyses non-traditional data, such as social media, geographic, rent payment records, and other data, to provide additional insights into potential payment behaviour (Ashofteh & Bravo, 2021). Information generated from digital activities such as browsing history, interactions on social media, mobile banking app usage, and e-commerce data. External data sources such as corporate data networks, credit agencies, or payment processing organisations are also leveraged to enrich information and predict credit risk.

ICS uses advanced technologies and analytics to analyse data and develop predictive models (Guo et al., 2019). Some technologies and analytics often used in ICS include big data analytics, machine learning, natural language processing (NLP), sentiment analysis and data visualisation (Kumar & Gunjan, 2020). Big Data Analytics utilises technology infrastructure and algorithms designed to process, store and analyse large volumes of data in real-time (Amalina et al., 2020). Machine Learning uses algorithms and artificial intelligence to identify complex patterns in data and make predictions based on previous experience (Basha & Rajput, 2019). Natural Language Processing (NLP) applies natural language processing techniques to recognise and understand the context of text data, such as customer reviews or social media posts (Sousa, 2022). Sentiment Analysis evaluates opinions, attitudes, and emotions in text or unstructured data, such as tweets or blog posts (Drus & Khalid, 2019). Data Visualisation uses interactive data visualisations; ICS helps to communicate analysis findings more intuitively and understandably (Battle & Scheidegger, 2020).

The ICS implementation process includes identifying objectives and needs, data preparation, model development, system integration, testing and evaluation and deployment and monitoring (Kang et al., 2021). Financial institutions should identify the specific goals and needs to be achieved by adopting ICS, such as improving the accuracy of credit risk assessment or increasing operational efficiency (Guo et al., 2019). The necessary data must be collected, cleansed and prepared for use in the ICS model. This may involve challenges such as format alignment, removal of missing data, or removal of irrelevant outliers. ICS models are developed using analytic techniques appropriate to the purpose and type of data used (Zhang et al., 2018). The process involves selecting essential variables, algorithm selection, model training, and validation. The ICS system should be integrated with existing information systems in the financial institution to ensure smooth data flow and quick and accurate assessment results (Giudici et al., 2020). The developed ICS model should be tested and evaluated using independent data to ensure good performance in predicting credit risk (Shen et al., 2019). Once the ICS model has been tested, financial institutions can apply it in their daily decision-making. This ICS implementation process should be accompanied by continuous monitoring and evaluation to ensure the model remains relevant and accurate (Edla et al., 2018).

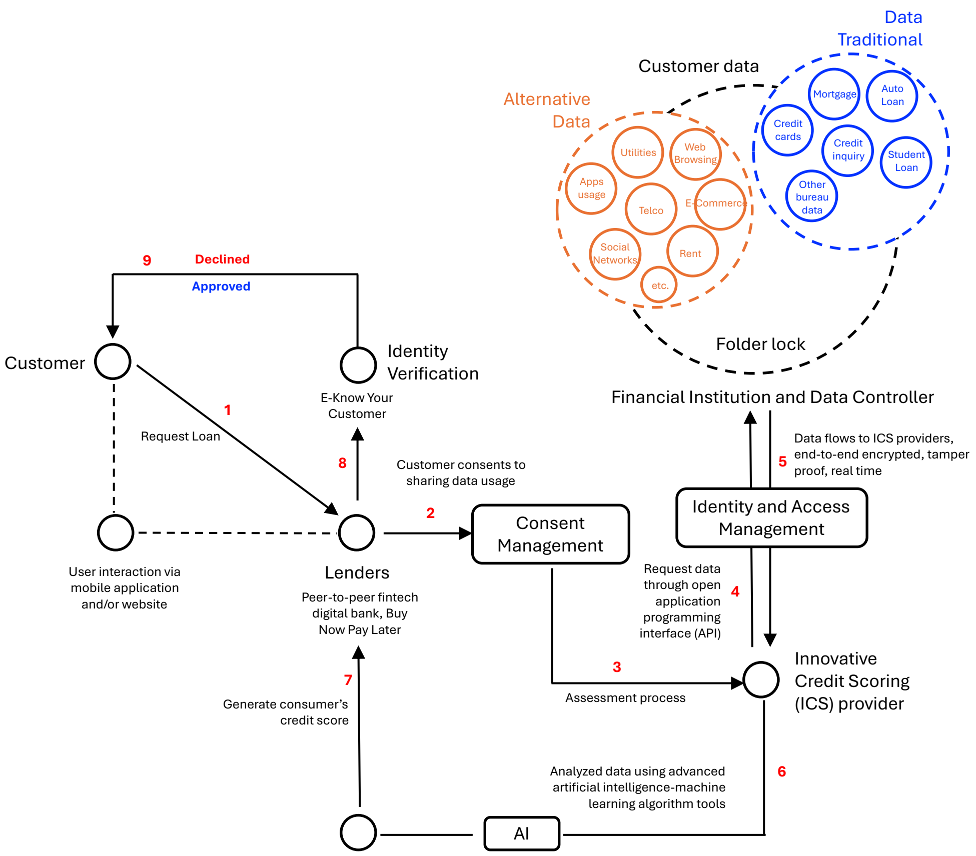

Figure 3. ICS Data Flow through API

Source: (Wijaya, 2023)

3 Research Methods

This research employs a qualitative approach with a case study as the primary research design. Additionally, desk research was conducted to gain a comprehensive understanding of concepts and theories related to Innovative Credit Scoring (ICS) and technology-based credit risk assessment. Primary sources include academic journals, books, and publications relevant to the financial industry. A literature review was used to identify research gaps and theoretical frameworks pertinent to this study. To strengthen the validity and reliability of the data, this research incorporated a more diverse range of secondary data sources to ensure robust triangulation. Specific data sources related to the company studied were included, such as company reports, annual reports, management presentations at events, company briefs, speeches by directors, and external media coverage (e.g., newspapers, online media, and industry-specific reports). These archival materials provided detailed insights into the company's practices and strategies in implementing ICS. By combining literature reviews with company-specific archival data, this study addresses both theoretical and practical aspects of ICS. The triangulation of various data sources enables a comprehensive exploration of the concept, its implementation, and the associated challenges and opportunities. The research methodology emphasises data credibility by selecting authoritative and reliable sources to provide an in-depth analysis of ICS within the case study context.

4 RESULTS AND DISCUSSION

4.1 ICS Implementation in the Financial Industry (Banks and Fintech)

The implementation of Innovative Credit Scoring (ICS) begins with the integration of advanced analytics and non-traditional data into the company's existing credit risk assessment processes. The company studied operates by collecting data from diverse sources, including customer behaviour, digital transaction history, and external social and economic indicators. This data is then processed through a technology-driven workflow involving data preprocessing, model training, and deployment. The workflow begins with data collection and validation to ensure accuracy and completeness. Once validated, the data is fed into machine learning algorithms designed to assess credit risk based on both traditional and non-traditional parameters. The models are periodically updated and refined using real-time data to improve predictive accuracy. The results of these models are integrated into the company's loan origination systems, enabling more precise credit decisions and streamlined approval processes. In the financial industry, ICS is used differently by banks and fintech companies. Banks tend to integrate ICS into their broader risk management frameworks, complementing traditional scoring methods. On the other hand, fintech companies often adopt ICS as their primary credit assessment tool, leveraging its ability to process non-traditional data sources and deliver quicker credit decisions. These differences highlight the flexibility of ICS and its adaptability to various organisational needs and structures. This detailed examination of the company's ICS activities and workflow provides essential context for understanding the subsequent challenges, opportunities, and regulatory considerations discussed in the following sections.

While one of the leading private banks in Indonesia has not yet formally implemented Innovative Credit Scoring (ICS), it has shown active support for the initiative led by the

Financial Services Authority (OJK) to integrate alternative data into credit assessments. This includes the potential use of data sources such as utility payments and social media activity to broaden the evaluation of creditworthiness. The bank has expressed its openness to collaborating with relevant stakeholders and regulators in exploring the application of alternative data to enhance credit risk assessments. Similarly, several other major state-owned banks in Indonesia have also conveyed their support for this initiative. Although the adoption of ICS remains in the exploratory stage, these institutions recognise its potential to improve credit scoring accuracy and enhance operational efficiency.

In the fintech sector, several companies have actively participated in testing ICS methods:

1. **P2P Lending Platform A** uses alternative data sources to assess potential borrowers. By analysing non-traditional data such as transaction histories and behavioural patterns, this platform aims to improve the inclusivity and accuracy of its credit assessments.
2. **P2P Lending Platform B** supports the use of alternative data in credit scoring to enhance access to financing for underserved communities. The company integrates data such as community engagement and financial habits into its assessment framework to build a more comprehensive credit profile.
3. **P2P Lending Platform C** views the adoption of ICS frameworks as a positive step toward expanding the reach and accuracy of borrower evaluations. The use of alternative data enables this platform to assess creditworthiness beyond traditional financial metrics, fostering greater financial inclusion.

These fintech companies illustrate the practical implementation of ICS in Indonesia's financial ecosystem. By leveraging alternative data and advanced analytics, they demonstrate how ICS can address gaps in traditional credit scoring systems. However, the specific outcomes and effectiveness of these implementations vary, depending on the business model, data availability, and regulatory environment. This case study highlights the cautious yet progressive approach of Indonesian banks and the proactive adoption of ICS by fintech companies. It underscores the importance of regulatory support and innovation in advancing credit risk assessment in the financial industry.

4.2 Challenges in Implementing Innovative Credit Scoring

One of the primary challenges in implementing Innovative Credit Scoring (ICS) is ensuring data security and privacy (Wijaya, 2023). Given the extensive data collection required by ICS, financial institutions face significant risks related to data leakage, cyberattacks, and privacy violations (Romanyuk, 2021). Banks and fintech companies like P2P Lending Platform A, B, and C must prioritise robust data security practices to protect sensitive information. This includes the use of data encryption, secure protection systems, and adherence to privacy regulations like the General Data Protection Regulation (GDPR) or relevant national data privacy laws (Gonçalves-Ferreira et al., 2019). Maintaining these standards is critical to ensuring that customer data is kept safe throughout the ICS process.

Another significant challenge is the risk of algorithmic bias in ICS models (Zhang & Qiu, 2020). Although ICS utilises analytics and machine learning to predict credit risk, the models can inadvertently perpetuate biases against certain groups if the data or the algorithm itself reflects inherent biases. For instance, if the data used by one of the leading private banks in Indonesia, P2P Lending Platform A, or P2P Lending Platform B reflects historical discrimination, it may result in unfair credit assessments (Seymour, 2018). To mitigate these risks, continuous monitoring and evaluation of ICS models are essential to identify and address potential biases. Transparency in algorithm development, variable selection, and adjustments is also necessary to ensure fairness (Eslami, 2021). This approach will help reduce the likelihood of bias and improve the overall integrity of the ICS process.

ICS implementation also faces challenges due to the lack of standardised practices (Novoselova et al., 2022). Currently, there is no universally recognised framework for ICS, which makes it difficult for institutions like one of the leading private banks in Indonesia, P2P Lending Platform A, P2P Lending Platform B, and P2P Lending Platform C to implement ICS effectively. Without clear standards and guidelines, the adoption of ICS could be inconsistent, leading to variations in model quality and outcomes. To overcome this, it is essential for the industry to collaborate on developing a standardised approach to ICS. This could involve cooperation between financial institutions, regulators, and research institutions to create a comprehensive framework that ensures ICS is applied consistently, while also addressing concerns like data security, algorithmic bias, and consumer protection (Chopra, 2021).

Furthermore, another challenge in ICS implementation is integrating qualitative factors into credit risk assessment (Donovan et al., 2020). While ICS primarily relies on quantitative data and predictive modelling, it often overlooks qualitative factors such as an individual's reputation, character, or unique economic circumstances. These factors, although harder to quantify, could provide valuable insights into a customer's creditworthiness (Liberati & Camillo, 2018). Financial institutions like one of the leading private banks in Indonesia, P2P Lending Platform A, and P2P Lending Platform B can overcome this by incorporating qualitative data through technologies like Natural Language Processing (NLP) to analyse customer sentiment, behaviour, and preferences. This would allow for a more comprehensive credit risk evaluation that accounts for both data-driven insights and human factors.

4.3 Opportunities and Benefits of Innovative Credit Scoring Implementation

One of the primary opportunities of implementing Innovative Credit Scoring (ICS) is the development of more accurate and predictive models for credit risk assessment (Pang et al., 2021). By leveraging advanced analytics and incorporating a wider range of data, financial institutions and fintech companies like P2P Lending Platform A, B, and C can enhance their ICS models beyond the limitations of traditional credit scoring methods. These improvements can lead to more precise predictions of credit risk, allowing for the identification of customers at higher risk of default, and ultimately reducing the occurrence of non-performing loans. ICS models have the potential to minimise the inherent subjectivity in traditional scoring systems, resulting in better-informed and more reliable credit decisions.

ICS also creates the opportunity for broader financial inclusion, allowing financial institutions like one of the leading private banks in Indonesia and fintechs to serve market segments that have traditionally been underserved by conventional financial services (Njuguna & Sowon, 2021). By utilising non-traditional data sources such as digital transaction patterns, social media activity, and online behaviour, institutions can assess creditworthiness for individuals with limited or no formal credit history. This is particularly advantageous for people who have not had access to traditional financial services, thus enabling both one of the leading private banks in Indonesia and fintech companies to serve a wider array of customers, many of whom might have been considered uncreditworthy by traditional criteria. This opportunity for expanded customer base helps promote more inclusive business growth and creates new market opportunities for financial institutions.

Implementing ICS also offers the benefit of enhancing the efficiency and quality of the credit risk assessment process (Melnyk & Borysova, 2019). By incorporating technology and automation, one of the leading private banks in Indonesia and fintech companies like P2P Lending Platform A, B, and C can accelerate the credit assessment process. This not only reduces reliance on human judgment, which is often prone to error, but also improves the consistency of credit decisions. Such improvements lead to reduced operational costs, higher productivity, and better allocation of resources, resulting in enhanced operational efficiency. With more accurate and automated credit risk assessments, these institutions can better prioritise loan applications, ensuring that riskier loans are identified and managed appropriately. This also leads to a reduction in non-performing loans and helps optimise the overall quality of the loan portfolio.

In addition, the implementation of ICS offers a substantial opportunity to improve the customer experience (Novoselova et al., 2022). By providing faster, more accurate credit assessments, financial institutions can make loan decisions more quickly. This increased speed not only enhances customer satisfaction but also strengthens the relationship between the financial institution and its clients. Moreover, with the help of ICS, one of the leading private banks in Indonesia can offer more tailored credit solutions such as competitive interest rates, higher credit limits, and flexible repayment terms. These personalised offerings not only improve the customer experience but also foster greater customer loyalty, creating a long-term, positive relationship between the institution and its clients. This shift towards a more responsive and customer-centric approach supports both one of the leading private banks in Indonesia and fintech companies like P2P Lending Platform A in maintaining a competitive edge in a rapidly evolving financial landscape.

4.4 Regulations and Framework for Implementation of Innovative Credit Scoring

The implementation of Innovative Credit Scoring (ICS) in credit risk assessment must adhere to applicable regulations to ensure compliance and maintain integrity within the financial industry (Guo et al., 2019). Financial institutions, including one of the leading private banks in Indonesia and fintech companies like P2P Lending Platform A, B, and C, must navigate a range of relevant regulations to implement ICS effectively and responsibly. One critical area of focus is data privacy regulations. Financial institutions must ensure that the data collected and used in ICS models complies with privacy standards and protects customer information. For example, data privacy laws such as the General Data Protection Regulation (GDPR) in the European Union are designed to safeguard personal data (Datoo, 2018). One of the leading private banks in Indonesia and fintech companies like P2P Lending Platform A need to adhere to local data protection laws to ensure that customer information is handled responsibly and securely, preventing data breaches and misuse.

Another key regulatory concern is anti-discrimination. ICS models must not discriminate against customers based on protected characteristics such as race, religion, gender, or marital status. Anti-discrimination regulations, similar to the Civil Rights Act in the United States, aim to prevent unfair treatment in credit decision-making (Hacker, 2018). For institutions, it is crucial that the data used and the algorithms powering ICS models are free from biases that could lead to discriminatory credit assessments. Regular monitoring and adjustments to the ICS models are necessary to ensure fairness and equal treatment for all customers.

ICS implementation must also consider capital and risk requirements established by financial regulators. Banks and fintech companies must ensure that their credit risk assessment models comply with the capital adequacy standards set by regulatory authorities such as the Central Bank or Financial Supervisory Authority (Danisman & Demirel, 2019). These institutions must maintain sufficient capital to manage potential risks arising from their credit portfolios, and ICS models should support prudent risk management practices that align with regulatory expectations.

Reporting and transparency requirements also play a crucial role in the successful implementation of ICS. Financial institutions like Bank and fintech companies must ensure that their use of ICS is transparent to both regulators and customers. They should comply with regulatory demands for reporting credit risk assessments and decision-making processes. Providing clear and transparent explanations of how ICS works—such as detailing the variables used in credit scoring models and how decisions are made—helps build trust and reduces customer uncertainty about the fairness of credit assessments.

To successfully implement ICS, an appropriate framework and code of conduct must be established to govern the use of technology and data in credit risk assessment (Edla et al., 2018). It is essential to consider several factors when developing this framework, including transparency, accountability, and social responsibility. Financial institutions must ensure they provide clear communication to customers about the credit risk assessment process, which will foster trust in the system. In addition, both bank and fintech companies like P2P Lending Platform A must pay careful attention to the ethical implications of their credit decisions (Óskarsdóttir et al., 2020). The use of ICS must be socially responsible, with a focus on minimising negative impacts and promoting fair outcomes.

Independent audits and checks are also critical for ensuring the integrity, accuracy, and reliability of the ICS models. Third-party audits help identify potential biases or errors in the models and provide a safeguard to maintain trust in the system (Luo, 2019). Furthermore, supervision and enforcement are necessary to ensure compliance with the established framework. Financial regulators should play an active role in overseeing ICS practices to ensure that they align with both regulatory requirements and ethical standards. In summary, one of the leading private banks in Indonesia, P2P Lending Platform A, and other financial institutions must implement a comprehensive framework and adhere to regulations to ensure the ethical, transparent, and responsible use of ICS in credit risk assessment. This approach will help ensure that ICS models enhance the integrity and accuracy of credit assessments while maintaining customer trust and compliance with applicable regulations.

5 CONCLUSIONS

Innovative Credit Scoring (ICS) offers significant potential benefits in credit risk assessment. Using advanced technology and non-traditional data, ICS can provide a more comprehensive understanding of a customer's credit risk profile, improve scoring accuracy, increase operational efficiency, and provide a better customer experience. While ICS offers potential benefits, various challenges and barriers need to be addressed in implementing ICS. These challenges include data privacy concerns, the risk of algorithm bias, shortcomings in considering qualitative factors, and the absence of standardised ICS practices. Overcoming these challenges requires attention to ethical aspects, privacy protection, and fairness in credit decision-making.

Implementing ICS has significant practical implications for the financial industry and customers. Some practical implications that can be identified include improved efficiency and customer experience, more accurate risk assessment and fairer and more inclusive access to credit. By utilising ICS, financial institutions can improve the efficiency of the credit risk assessment process, reduce loan approval time, and speed up customer service. This helps meet the expectations of customers who want a quick and easy loan experience. ICS enables a more holistic and in-depth analysis of a customer's credit risk profile by considering various relevant data factors. With higher assessment accuracy, financial institutions can reduce the risk of non-performing loans and improve the quality of their loan portfolio. Through non-traditional data, ICS can help create greater access to loans for individuals or segments of the population previously unreachable by traditional financial institutions. This can increase financial inclusiveness and provide opportunities to underserved groups.

Several recommendations, including cooperation between financial institutions and technology companies, regulatory monitoring and oversight, consideration of ethical aspects and algorithm bias, and validation and verification frameworks, can improve the implementation and development of ICS. Financial institutions can establish strategic partnerships with technology companies to capitalise on technological advances and gain access to non-traditional data required for ICS. Such collaborations can accelerate innovation and improve credit risk assessment capabilities. Financial regulators have an essential role in monitoring industry practices related to ICS. Appropriate regulations and standards must be developed to ensure fairness, data privacy compliance, sound risk management and consumer protection. Financial institutions should pay attention to ethical aspects and avoid algorithm bias in developing and implementing ICS. Ensuring that ICS models do not discriminate and maintain fairness in credit decision-making is essential. Banks and financial institutions should adopt an appropriate framework for validating and verifying ICS models. Thorough testing and validation should be conducted periodically to ensure the reliability, accuracy and soundness of the model and credit risk assessment process.

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