Innovative Credit Scoring Regulation in Indonesia: too Little, too Late?

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Abstract, Design/methodology/approach – This paper uses a qualitative approach by analyzing credit scoring regulations in Indonesia. Data sources are primary legal material in the form of statutory regulations and secondary legal material in the form of literature from scientific journal articles, books, and other sources related to credit scoring.
Purpose – Innovative credit scoring is a solution for scoring potential borrowers who have no credit history. This paper examines the regulatory issue of innovative credit scoring because there are no regulations that specifically regulate this approach in Indonesia.
Findings – There are no regulations that specifically regulate innovative credit scoring in Indonesia.
Practical implications - This paper emphasizes the importance of special regulations for innovative credit scoring involving the banking industry, society, business actors, and innovative credit scoring actors.
Originality/value – Discussions about innovative credit scoring are relevant today because approaches that use non-traditional data are interesting in credit scoring. This investigation helps illustrate attention to the importance of alternative credit scoring.

Keywords: innovative credit scoring, credit scoring, regulatory sandbox, self-regulation, machine learning

1. Introduction

The Google and Temasek report (2019) states that the Indonesian population is categorised as banked (23%), underbanked (26%), and unbanked (51%). Underbanked and unbanked are groups with low or unserved financial inclusion in financial services. There are 92 million adults in Indonesia who are underserved by financial services (Wijaya, 2023).

On one hand, banks will only provide access to banked groups that have a credit history through credit scoring. On the other hand, credit scoring is widely used to measure credit risk in the financial industry (Vasconcellos et al., 2019). Conventional credit scoring models are only evaluated based on predictive accuracy or profitability (Hurley & Adebayo, 2016).

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Thus, groups with no credit history will find it difficult to access loans as there is no data available for scoring (Niu et al., 2019). In addition, the risk assessment between customers with no credit history is equated with customers with poor credit history. Hence, individuals with no credit history will receive poor scoring. This underserved group will then seek other access to finance, such as peer-to-peer lending (Hidajat, 2019; Hidajat et al., 2016), or other sources with high interest rates.

One of the challenges that arises in credit scoring is how to find potential borrowers who have no credit history but have high accuracy, because traditional and quantitative methods of assessing potential borrowers only benefit the banked group.

Innovative credit scoring (ICS) is one of the solutions to overcome this problem. Unlike conventional credit scoring that uses the 5C Principles, ICS uses artificial intelligence (AI), machine learning and non-traditional data to assess the creditworthiness of customers who have limited access to financial services.

Credit scoring is increasingly developing by utilising AI (Thomas, 2000) such as machine learning and producing more accurate and efficient models (Dastile et al., 2020). Machine learning is an AI application that uses statistical techniques to generate models from a set of data.

Since the 2008 financial crisis, alternative credit scoring has seen significant growth in Europe and North America. The utilisation of credit scores in peer-to-peer lending by large fintech companies to handle the risk of default of potential borrowers has even grown tremendously. Currently, fintech are using big data technology to help process prospective borrowers (Campbell-Verduyn et al., 2017).

Some uses of machine learning for credit scoring include the use of Random Forest, AdaBoost, and LightGBM to predict the chances of default in peer-to-peer lending using social network information in China (Niu et al., 2019), random forest to assess the effectiveness of the credit union lending process in Brazil (Vasconcellos et al., 2019), Naive Bayesian Model, Logistic Regression Analysis, Random Forest, Decision Tree, and K-Nearest Neighbor Classifier for bank loans in China (Wang et al., 2020).

The use of non-traditional methods in scoring allows ICS to not only assess individuals with no history to access credit, but also improve the ability of lenders to assess risk. By comparing conservative credit scoring models with machine learning methods, Ashofteh & Bravo (2021) found that machine learning provides better results. Bitetto et al. (2023) who compared classical parametric and non-parametric approaches also showed that machine learning provides better results.

Several studies have shown that ICS provides benefits in the financial industry. ICS helps lenders better assess the lending needs of micro, small, and medium enterprises. The more than 64 million MSMEs in Indonesia are the largest number of borrowers that benefit from ICS (Wijaya & Nidhal, 2023). ICS also plays a role in increasing access to finance, especially for the unbanked and underbanked (Allen et al., 2021).

The challenge is that ICS is something new and emerging in Indonesia. As of early 2024, there are 19 ICS companies in Indonesia. But until now, there is no regulation specifically governing ICS in Indonesia. In fact, financial innovation requires regulations that are adaptive and able to mitigate risks.

This paper discusses regulations related to ICS in Indonesia. The discussion of ICS is relevant today because approaches that use non-traditional data are interesting in credit assessment (Ceylan & Elif, 2018). This paper uses a qualitative approach by analysing ICS regulations in Indonesia. Data sources are primary legal materials in the form of laws and regulations and secondary legal materials in the form of literature from scientific journal articles, books and other sources related to credit scoring.

2. ICS Regulations and Policies in Indonesia

The Indonesian government through Otoritas Jasa Keuangan (OJK) as the Financial Services Authority recognises the existence of ICS by issuing several regulations. These regulations are made to ensure that the industry develops responsibly. Some of these regulations are Financial Services Authority Regulations 77/POJK.01/2016 and 13/POJK.02/2018, Bank Indonesia Regulations 19/12/PBI/2017 and 23/2/PBI/2021.

Table 1. Regulations Related to ICS

Regulations	Regulations Contents
Financial Services Authority Regulation 77/POJK.01/2016	Information technology-based lending and borrowing services.
Regulatory Sandbox:	
• Bank Indonesia Regulation 19/12/PBI/2017	Implementation of financial technology.
• Financial Services Authority Regulation 13/POJK.02/2018	• Issued and effectively implemented as regulations related to digital financial innovation to support the development of digital finance, including ICS; • Regulations related to regulatory sandbox mechanisms.
Self-Regulation:	
• Code of Conduct	Efforts to avoid irresponsible practices, fill legal gaps and to prioritize and maintain consumer protection.
• Code of Ethics	Directions for fintech company members to conduct business responsibly.
Bank Indonesia Regulation 23/2/PBI/2021	Principles of risk-based credit assessment, including the use of credit scoring.
Law Number 27/2022	• Regulations governing consumer data protection; • Regulations related to the establishment of a Data Protection Authority.
Law Number 4/2023	• Legal certainty of Financial Sector Technology Innovation; • Institutional relations between regulators and Financial Sector Technology innovation actors and associations; • ICS as market support.

In 2016, the Financial Services Authority issued OJK Regulation 77/POJK.01/2016 on Information Technology-Based Money Lending and Borrowing

Services. This regulation became the foundation of the P2P lending industry in Indonesia by outlining the requirements for implementation.

Subsequent regulations govern the regulatory sandbox, namely Bank Indonesia Regulation 19/12/PBI/2017 on the Implementation of Financial Technology, and Financial Services Authority Regulation 13/POJK.02/2018 on Digital Financial Innovation in the Financial Services Sector. Regulation 13/POJK.02/2018 is the legal basis for OJK to regulate digital financial innovation in the financial services sector and identify clusters of digital financial innovation including innovative credit scoring. The government uses the regulatory sandbox as a testing mechanism to assess the reliability of business processes, business models, financial instruments, and governance of parties organising digital financial innovation.

In 2021, a new regulation emerged, namely Bank Indonesia Regulation Number 23/2/PBI/2021 on Risk-Based Credit Assessment which regulates the principles of risk-based credit assessment.

2.1. Regulatory Sandbox

ICS is a new and emerging industry in Indonesia. To date, there are no regulations specifically governing ICS. Through the Financial Services Authority as the financial services regulator, the government uses regulatory sandbox as a testing mechanism to assess the reliability of business processes, business models, financial instruments, and governance of parties organising digital financial innovation.

Currently, the regulatory sandbox is regulated in two regulations, namely Financial Services Authority Regulation Number 13 /POJK.02/2018 on Digital Financial Innovation in the Financial Services Sector and Bank Indonesia Regulation 19/12/PBI/2017 on the Implementation of Financial Technology.

According to the Financial Services Authority Circular Letter Number 21/SEOJK.02/2019 on Regulatory Sandbox, the regulatory sandbox aims to ensure that digital financial innovations fulfil several criteria. These criteria are being innovative and forward-looking; using information and communication technology as the main means of providing services to consumers in the financial services sector; supporting financial inclusion and literacy; useful and widely usable can be integrated into existing financial services; using a collaborative approach; and paying attention to aspects of consumer protection and data protection.

Based on Bank Indonesia Regulation 19/12/PBI/2017, regulatory sandbox is a safe, limited trial space to test financial technology providers and their products, services, technology, and/or business models. The scope of fintech in this regulation includes the use of technology in the financial system that produces new products, services, technology, and/or business models and can have an impact on monetary stability, financial system stability, and/or the efficiency, smoothness, security, and reliability of the payment system.

Basically, the regulatory sandbox at OJK and BI are similar in both form and purpose. Both are created to ensure that innovations in the financial services sector still follow established regulatory procedures without limiting existing innovations.

The fundamental difference between the regulatory sandbox at OJK and BI is the object of the trial. Regulatory sandbox in OJK is conducted on digital financial innovation providers in a broader scope, while in Bank Indonesia it is conducted on financial technology providers specifically for payment systems.

2.2. Self-Regulation

Self-regulation is the transfer of regulatory responsibility to a party other than the government (Cohen & Sundararajan, 2015). The Financial Services Authority delegates the supervisory function of ICS to the fintech association affiliated with this industry, namely the *Indonesian Fintech Association (AFTECH).*

AFTECH is an association of business actors officially appointed by OJK on 19 July 2019 as the official association of digital financial innovation providers based on POJK No. 13/2018. *AFTECH* membership is mandatory for ICS service providers. This organisation plays an important role for consumers and ICS as it is responsible for consumer complaint handling procedures. The organisation also works with several associations such as the *Indonesian Joint Funding Fintech Association (AFPI*) and the *Indonesian Sharia Fintech Association (AFSI).*

AFTECH is authorised to independently develop regulatory instruments, monitor compliance, and ensure implementation by its members. *AFTECH* regulates ICS compliance through two main policy instruments, namely the Code of Conduct related to personal data protection and data confidentiality in the financial technology sector, and the Code of Conduct for fintech providers in the financial services sector, financial planners, innovative credit scoring and aggregators.

2.2.1. Code of Ethics

Consumer protection is one of the prerequisites for the growth of the fintech industry. *AFTECH* has included consumer protection as a priority issue since 2017. *AFTECH* is tasked with drafting a general and specific code of conduct for each business model that falls under the scope of digital financial innovation. This code of conduct is a direction for fintech companies to conduct business responsibly.

The code of conduct for personal data protection is based on the regulation of the Minister of Communication and Information Technology Regulation No. 20/2016 on the Protection of Personal Data in Electronic Systems, and Government Regulation No. 71/2019 on the Implementation of Electronic Systems and Transactions. This code of conduct is intended to establish a code of conduct for the treatment of personal data in the fintech sector; establish general principles and steps to be taken by fintech providers to ensure that the processing of personal data does not violate the rights of data owners; and serve as a framework for monitoring and enforcing compliance of fintech providers.

In general, this code of conduct also aims to provide certainty to consumers as owners of personal data, increase public trust in the financial technology industry, and demonstrate a commitment of responsibility to the government and other financial service players in digital financial innovation.

2.2.2. Code of Conduct

The ICS Code of Conduct is an effort to avoid irresponsible practices, fill legal gaps and to promote and maintain consumer protection as an effort to implement and monitor good market conduct principles.

The Code of Conduct is a set of principles and processes established by mutual agreement of the members that are binding on all members of the association. The Code is a guide to ethical and responsible behaviour for providers offering ICS services. The code of conduct was developed based on the basic principles of integrity and quality of credit scores that can be accounted for, transparency of data sources and data processing, independence, and security standards.

The code of conduct also contains an article on sanctions. Organisers who do not comply with the provisions in the code of conduct will be subject to administrative sanctions including written warnings, publication of violators to OJK and the public, and temporary or permanent dismissal as members of the association. The imposition of sanctions at the discretion of the Association's Ethics Committee is based on the frequency of violations, the impact resulting from violations, elements of intent and negligence, and other factors deemed relevant.

3. Discussion

3.1. ICS Challenges in Indonesia

ICS benefits not only borrowers, but also lenders. There are many opportunities that can be utilised such as the vast market and big data that is utilised for machine learning. However, in addition to providing benefits, ICS also contains risks. According to Wijaya (2023), the risks inherent in ICS include customer data leakage, artificial intelligence bias, and market control.

i. User data leakage

Ensuring consumer protection and providing regulations that are adaptive to innovation is one of the main challenges of fintech (Rumata & Sastrosubroto, 2020). ICS has a large amount of customer data that has the potential for data leakage. Sources of risk can come from cyberattacks, human error, internal security breaches, reliance on third-party services, lack of device security, violation of data privacy regulations, lack of employee security training and awareness, and loss or theft of devices.

Data leaks can create the risk of privacy breaches, leading to identity theft and misuse of information. Victims of data leaks may feel the discomfort and annoyance of losing control of their privacy and their personal information no longer being private. Data leaks often give access to unauthorised parties to steal individuals' identity information, and misuse to commit various types of fraud.

Despite ongoing data protection efforts, concerns regarding the use, collection and storage of consumer data are still alarming as small loopholes can lead to massive data leaks (Varshney et al., 2020). The growth of digital services is not only about the huge potential of technology in adding value to society but also the important role of trust in driving digital adoption (DS Innovate, 2022).

Financial services is one of the most vulnerable sectors to crime and data breaches. According to *Checkpoint Research* 2022, the financial services sector faces 1,131 cyber-attacks every week. Some data leakage cases include *Bank Indonesia* (2022), *BRI Life* (2021), *Bank Jatim* (2021), and fintech *Cermati.* In January 2022, a cyber-attack from a ransomware group called *Conti* allegedly stole Bank Indonesia data. In July 2021, the data of two million *BRI Life* customers and 463,000 documents were hacked. In October 2021, hackers stole customer data, employee data, and personal financial data of *Bank Jatim* customers, and sold the data on forums. *Cermati* fintech data was also hacked in the form of email addresses, home addresses, telephone numbers, income, id, occupation, company name, and customer's mother's name (Rini, 2023). Another data theft case was experienced by the *Tokopedia* and *Bukalapak* marketplaces. A total of 91 million *Tokopedia* data were leaked and distributed on internet forums. Data of 13 million *Bukalapak* users were hacked and sold on the dark web (Kusuma & Rahmani, 2022).

The risk of customer data protection arises because there is no regulation that clearly regulates the party responsible for data use violations. For example, no decision has been made on who is responsible for the data leak case in August 2022.

ii. Artificial intelligence/ machine learning bias

The principle of fairness without discrimination is one of the fundamental challenges in AI and machine learning. AI can be used in many fields to make important and life-changing decisions, so the system's decision-making should not give rise to discriminatory behavior against certain populations or groups (Mehrabi et al., 2021).

AI technology provides hope for the development of credit scoring, but the existence of bias remains a challenge in making lending decisions (Kumar et al., 2021). After all, AI is created by humans, which apart from being imperfect also contains biases that can influence credit assessments (Mehrabi et al., 2021).

Algorithms in AI and machine learning are becoming critical components in decision making in various sectors, including finance. However, like any technology, these algorithms are susceptible to biases that can influence the outcome of financial decisions.

These biases include data bias, algorithm bias and socio-economic bias. Data bias caused by the quality of the data used in machine learning is a key factor in determining model performance. Machine learning algorithms learn from historical data to make predictions or decisions for the future. Historical data that may be incomplete, unbalanced, or reflect social inequalities can introduce significant bias.

Complex and non-transparent algorithms can produce decisions that are difficult to explain. Additionally, selecting an inappropriate algorithm for a particular task or inappropriate parameters can lead to biased results.

In socio-economic bias, the use of artificial intelligence in financial decision making is often within a complex socio-economic context. Factors such as economic inequality, differences in access to financial services, and individual preferences can influence the outcome of financial decisions. The tendency not to take these factors into account can result in unfair or suboptimal decisions.

The use of unfair or inaccurate models due to these biases, can result in inequities in access to financial services, inappropriate risk taking, or unfair denial of credit. Additionally, bias in financial decisions can also lead to financial losses for affected individuals or entities.

For example, Putri & Lestari (2016) who studied six Javanese couples concluded that they shared roles in three areas, namely decision making, family financial management and childcare. The husband's role is greater in decision making, while the wife's is in financial management and childcare. This condition can cause bias because women who manage their finances on a daily basis but do not have a savings account can get a bad score.

Pagano et al. (2023) proves that there is still a bias problem in machine learning. Mehrabi et al. (2021) who surveyed many applications also showed that there is bias through various methods. In fact, discriminatory systems not only harm certain individuals or groups, but also disrupt the development of AI and machine learning.

Such discrimination in financial services has far-reaching impacts on underrepresented consumers (Bone et al., 2014). The discriminatory impact of AI-based decision making on certain population groups is evident in various cases (Ntoutsi et al., 2020). Rosenman et al. (2011) found that gender and race or ethnicity were related to the amount of bias. For example, data-based decision making used in the justice system to inform decisions about bail, parole, and prison sentences is biased against historically marginalized groups (Angwin et al., 2022).

iii. Market domination

Collaboration between companies that own data that dominate the market can lead to restrictive business practices and unfair competition. Companies that control data have the power to control prices and access to markets. They can use this power to limit competitors' access or set prices to the detriment of customers.

By limiting access to the vast amounts of data they hold, these dominant players can create barriers for new entrants and smaller competitors, ultimately reducing consumer choice. In addition, this kind of collaboration can lead to the formation of oligopolies or even monopolies that further strengthen control over the market (Duch-Brown et al., 2017).

Additionally, the restrictive business practices of collaborative data ownership also negatively impact data privacy and security. When large players combine their data sets, the risk of data breaches and misuse increases, potentially compromising consumer data (Schneider et al., 2017).

3.2 Regulatory Evaluation

The growing number of digital financial innovation organizers is a form of progress in digital financial innovation and the financial technology market which is increasingly developing in Indonesia (Indonesian Fintech Association, 2020). The growth of digital banks and online lending platforms since 2016 in Indonesia has been an important period in the development of the ICS industry. P2P lending and ICS emerged in Indonesia as a response to the high number of populations classified as unbanked and underbanked, especially in rural areas (Google, 2021).

This growth raises challenges and risks because financial technology is rapidly innovating. Regulating a disruptive industry like fintech is not easy because most existing regulations are based on traditional business practices. So, fintech developments that are not accompanied by regulatory changes can create the risk of policies that do not accommodate innovation or even hinder it (Bukht & Heeks, 2017).

The Indonesian government through the Financial Services Authority recognizes the importance of ICS through several regulations. Several of these regulations show that the government has taken steps to ensure that this industry develops responsibly. However, this condition shows that the Indonesian government appears to be late in responding to ICS developments. Regulations emerged as the industry grew. According to Wijaya & Nidhal (2023), Indonesian regulations have difficulty keeping up with new technological developments related to collecting and assessing the quality of alternative data.

The development of ICS has also not been accompanied by regulations that specifically regulate ICS. However, this is understandable because artificial intelligence and machine learning are so dynamic that a rigid and bureaucratic regulatory approach is often inappropriate. Companies prefer to use methods based on their respective conditions.

OJK, in collaboration with the Indonesian Fintech Association, is completing efforts to supervise fintech entities through self-regulation in the form of behavioral guidelines and codes of ethics for ICS organizers. As a regulator, the Financial Services Authority (OJK) uses a joint regulatory approach (coregulation), by establishing a regulatory sandbox. However, existing regulations do not yet have a clear mechanism regarding the flow and stages after the regulatory sandbox, ICS licensing in the digital financial ecosystem, regulations regarding business rules and standardization, as well as ICS governance and institutional design. This could hinder the development of ICS in Indonesia, when partnering with financial sector service players.

Self-regulation in credit assessment also has several weaknesses that can affect the fairness and accuracy of credit assessment. One of the main weaknesses is the lack of consistency and standardization across various credit scoring models. Without a uniform set of guidelines and regulations, different rating agencies may use different criteria to evaluate creditworthiness, resulting in varying results for individuals with similar financial profiles (Spader, 2010).

Self-regulation may create potential conflicts of interest, as credit rating agencies may prioritize their own profits over the accuracy of their assessments. This can result in biased credit assessments, further exacerbating gaps in financial access.

Additionally, a lack of transparency in self-administered credit scoring can limit consumers' understanding of how their scores are calculated and the specific factors that influence their creditworthiness. This lack of clarity can erode trust in the credit scoring system. Self-regulation may also fail to address the complexity and risks in the financial sector.

4. Conclusion

The Indonesian government recognizes the importance of ICS by issuing several regulations related to this industry. This regulation issued by the OJK and Bank Indonesia is to ensure that the financial industry develops responsibly. Apart from that, the government also uses self-regulation as a testing mechanism to ensure digital financial innovation meets the criteria. Codes of ethics and codes of conduct also complement regulations so that this industry develops well.

Several of these regulations show that the government has taken steps to ensure that this industry develops responsibly. However, this condition shows that the Indonesian government appears to be late in responding to ICS developments. Regulations related to ICS emerged after the industry grew.

This condition is paradoxical, because on the one hand, fintech developments that are not accompanied by regulations can create risks, but on the other hand, disruptive industries such as fintech must be adaptive and not regulated by rigid regulations. Self-regulation also has several weaknesses that can affect the fairness and accuracy of credit assessments due to a lack of consistency and standardization across assessment models, potential conflicts of interest, and a lack of transparency in credit assessments.

The solution to the ICS problem in Indonesia is to create special regulations for ICS involving the banking industry, society, business actors and ICS actors. The challenge is to create regulations that are not rigid but remain adaptive because the development of artificial intelligence and machine learning is very dynamic.

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