



A shopkeeper arranges items in her store in Cianjur, Indonesia.
Photo: J-PAL SEA

FEBRUARY 2025

INNOVATIVE CREDIT SCORING: UNLOCKING FINANCIAL OPPORTUNITIES FOR MICRO, SMALL, AND MEDIUM ENTERPRISES

This landscape memo synthesizes insights from rigorous evaluations, stakeholder interviews, and grey literature (reports, news articles, policy literature, and government documents) to assess the opportunities and challenges of innovative credit scoring (ICS) in improving financial access for micro, small, and medium enterprises (MSMEs) in Indonesia. It also highlights key research questions critical to advancing ICS development.

Jing Cai, Arya Gaduh, Maria Valencia Elita Sarah

This document was prepared by the J-PAL Innovation for the Micro, Small, and Medium Enterprise Development Initiative (IMDI) team in affiliation with J-PAL Southeast Asia to summarize existing global literature on innovative credit scoring (ICS) and provide an overview of the ICS landscape in Indonesia based on stakeholder interviews and grey literature. It is not an exhaustive review of all the rigorous evidence on this topic.

TABLE OF CONTENTS

INTRODUCTION	2
SECTION 1. THE LANDSCAPE OF MSMEs' FINANCIAL ACCESS	3
1.1 MSMEs' financing needs	3
1.2 Challenges faced by MSMEs in accessing finance	3
1.3 The traditional credit scoring method	4
SECTION 2: PROMISING INNOVATION: INNOVATIVE CREDIT SCORING	8
2.1 Overview	8
2.2 Implementing ICS.....	8
2.3 The opportunities of using ICS	11
SECTION 3: KEY POINTS FOR CONSIDERATION	14
CONCLUSION	18
REFERENCES	20

INTRODUCTION

In Indonesia, micro, small, and medium enterprises (MSMEs) play a vital role in the economy by creating employment opportunities and driving economic growth (Kristanus 2023). Despite their significant contributions, many MSMEs face credit constraints because of their limited credit history and a lack of collateral resulting in high screening and monitoring costs for lenders. This memo explores innovations to expand MSMEs' financial access by introducing novel methods to evaluate their creditworthiness.

Many MSMEs struggle to acquire financial capital to increase their productivity and expand their business. The Government of Indonesia has prioritized improving MSMEs' financial access through various policies and credit programs. On the latter, it has introduced several credit programs for MSMEs, including the People's Business Credit (KUR), Ultra Micro Financing (UMi), Fostering a Prosperous Economic Family Program (PNM Mekaar), and Unit Service for Micro Capital (PNM Ulamm) (Cai et al. 2024). At the same time, the Central Bank of Indonesia (BI) issued regulations that require financial institutions to disburse 30 percent of their credit share to MSMEs by 2024 (BPK 2021). Nonetheless, the number of micro and small firms in the manufacturing industry that are borrowing from banks as their main source of capital remains low at 2.2 percent in 2023 (Badan Pusat Statistik 2024).¹ MSMEs' limited credit history and lack of collateral introduce high risks for banks and other institutions looking to lend to MSMEs (Puspadini 2024). As a result, most financial institutions either refuse to lend to MSMEs or can only offer loans with high interest rates and/or collateral requirements. These are typically small loans, with the vast majority (94.59 percent) having a value of below 20 million rupiah (Badan Pusat Statistik 2024).

To support MSME growth, in 2022, the government started to explore innovative credit scoring methods (ICS) (Antara News 2024b). ICS firms offer an alternative way to measure credit scores of people who have never borrowed from banks: instead of relying solely on previous credit repayment data, they combine a rich set of data sources – such as cell phone bills, e-commerce, social media, and household bill data – with machine learning algorithms to construct a credit score (Wijaya 2023). The use of ICS has grown rapidly in recent years, with more ICS firms flourishing in Indonesia and more financial technology (fintech) lending firms adopting it (Wijaya 2023). However, more research is needed to measure the impact of ICS methods on lending decisions.

In this memo, we outline the credit landscape, the evolution of ICS, rigorous evaluations of its impact on MSME financing, and key considerations for supporting ICS development in Indonesia. **The memo is primarily based on insights from interviews with key stakeholders,**

¹Manufacturing industry refers to the sectors involved in the production of goods by transforming raw materials or lower-value goods into finished/semi-finished or higher-value goods. It includes sectors such as food production, textiles, machinery, apparel, tobacco, and non-metallic mineral products (Badan Pusat Statistik 2024).

including ICS representatives, lending institutions, and industry experts. Section 1 discusses the state of MSMEs' financial access. Section 2 elaborates on the innovations to support their financial access, with a focus on ICS, including its opportunities and challenges. Finally, Section 3 covers key considerations that need to be taken into account when implementing ICS to further expand MSMEs' financial access.

This memo is intended to be a reference document for the government and donors interested in enhancing financial access for Indonesian MSMEs through innovative approaches. It also aims to provide a resource for researchers interested in filling the current knowledge gap around improving MSMEs' financial access through ICS.

SECTION 1. THE LANDSCAPE OF MSMEs' FINANCIAL ACCESS

1.1 MSMEs' FINANCING NEEDS

MSMEs require access to capital to start, maintain, and grow their business. Initially, they may need capital to purchase equipment and inventory. As they expand, additional financing can help them scale operations, cover short-term needs—such as participating in marketing exhibitions or fulfilling orders—and seize growth opportunities. While loans are crucial for business growth, many MSMEs struggle to secure financial capital. In 2023, only 2.2 percent of micro and small firms in the manufacturing industry, a key sector in Indonesia's economy due to its potential to produce higher-value goods, received loans from banks as their main source of capital for their business (Badan Pusat Statistik 2024). A recent report by the World Bank's International Finance Corporation found that Indonesia's estimated MSME financing gap is currently at US\$234 billion (International Finance Corporation 2024).

1.2 CHALLENGES FACED BY MSMEs IN ACCESSING FINANCE

Both demand and supply constraints are responsible for the MSME financing gap. **From the demand side, take-up rates of loan products are low for MSMEs because existing credit options do not adequately meet their needs.** Previous studies have found that most MSMEs do not borrow from banks due to obstacles like high interest rates, collateral requirements, inflexible repayment time frames, and complex application processes (International Finance Corporation 2016; Badan Pusat Statistik 2024; 60decibels 2024). Digital lending has since emerged as an alternative borrowing option, primarily because of its streamlined application process.² Although more accessible than traditional banks, the proportion of MSMEs borrowing from digital lenders remains low. As of 2023, MSMEs account for 36.57 percent of the total lending portfolio among peer-to-peer (P2P) lenders (AFPI 2023). The low take-up rate may be due to recent cases of fraud

² AFPI, interview by Bertha Fania Maula, Ahmad Jibril, and Maria Sarah, 24 May 2024.

associated with illegal lending, which led to a negative stigma surrounding “online lending” (*pinjaman online/pinjol*) and increased mistrust of legitimate digital lenders that have been certified by the Financial Services Authority (OJK). Low levels of digital literacy may also hinder understanding of the differences between legal and illegal platforms, making it difficult for individuals to navigate these options effectively.³ Consequently, entrepreneurs are discouraged from seeking loans from lending institutions and will resort to self-financing or borrowing from friends and family (Cai et al. 2024, 60decibels 2024, International Finance Corporation 2016).

Moreover, **many credit options fail to meet the needs of women entrepreneurs, who make up the majority of micro and small-firm owners.** More than 70 percent of these micro and small firms are owned and led by women (Badan Pusat Statistik 2024). However, 82.3 percent of women entrepreneurs cite inadequate working capital as a major barrier to growth (IIX Global 2024). Despite having lower default rates than men-owned MSMEs, women entrepreneurs still face gender bias in financing (IIX Global 2024). For example, only 20 percent of impact investments went to women-led businesses in 2020 (Purnamasari et al. 2023). Factors that contribute to the imbalance include pre-existing socio-cultural barriers, perceived risks of limited business expertise, lack of credit history, and low financial literacy. Additionally, collateral requirements often further disadvantage women’s access to financing since assets are usually registered under the male family members’ name (IIX Global 2024). Women in rural and economically underserved areas face even more limited access to financial resources compared to urban areas (IIX Global 2024).

On the supply side, one of the lenders’ main constraints is their inability to assess the risk profile of MSMEs with no prior formal loans and that are absent from the general credit data registry, the Financial Information Service System (SLIK), hosted by OJK (Sutrisno 2024). Financial institutions use a credit score to assess an applicant’s creditworthiness and their likelihood to repay their loan on time. Traditional credit scores use indicators such as a person’s payment history of previous credit borrowed, amounts owed, length of credit history, credit mix, and new credit applications to capture an individual’s willingness and ability to pay (World Bank 2019). MSMEs without prior formal loans would lack such information and would therefore struggle to access formal financing. Moreover, banks lack sufficient incentives to lend to MSMEs, whom they often view as higher-risk clients. An ongoing OJK draft regulation encourages but does not require, financial institutions to have 30 percent of their credit share allocated for MSMEs (Simanjuntak 2024).

1.3 THE TRADITIONAL CREDIT SCORING METHOD

There are three main sources of traditional credit scores available to lenders. First, they can gather credit information from SLIK, which is issued by OJK (OJK 2024e). These reports provide credit histories and financial information of the applicants, that are used by traditional banks to construct a credit score. Second, they can also get credit information from credit reports, which are issued by

³AFPI, interview by Bertha Fania Maula, Ahmad Jibril, and Maria Sarah, 24 May 2024.

credit bureau agencies. Third, fintech lending institutions—whose loans typically have shorter tenors than traditional banks—can refer to the Pusdafil database by OJK, which compiles borrowers of fintech loan products. Additionally, the Indonesian Joint Funding Fintech Association (AFPI) developed and created the Fintech Data Center, which centralizes and streamlines credit information for its members, allowing access to applicant data from fintech lending institutions (see Table 1 for a detailed description of the databases)⁴.

TABLE 1. EXISTING DATABASE FOR CREDIT INFORMATION

DATABASE	FUNCTION	DATA TYPE	ACCESS	UPDATE MECHANISM AND FREQUENCY
SLIK OJK	Financial institutions can use the information to assess a client's creditworthiness and make lending decisions.	Applicant's credit history, and data on collateral and related information from various financial institutions, public, credit bureau (LPIP), etc.	SLIK data can be publicly requested and accessed by individuals or businesses.	Data is submitted by traditional and non-traditional financing institutions. The database is updated monthly.
Credit Bureau Services Credit Bureau Agencies (PEFINDO, PT CLIK, Credit Bureau Indonesia)	Produces credit reports and scores for individuals and companies. The credit report can be used by non-financial institutions to determine potential consumers' worthiness to be offered insurance, TV subscription,	Credit reports include personal information, payment history, total amount of debt, length of credit history, and types of credit you have.	Credit reports can be accessed through credit bureau agencies, or other organizations that partner with these agencies such as Skorlife. Credit reports can be requested and accessed by	Credit reports include data collected from various institutions, including commercial banks, rural banks, credit-providing financial institutions, and securities financing institutions. As per OJK Regulation No. 64/POJK.03/2020 , required institutions must submit debtor information to OJK on a monthly basis.

⁴Ibid.

DATABASE	FUNCTION	DATA TYPE	ACCESS	UPDATE MECHANISM AND FREQUENCY
	internet, utilities, or post-pay phone, etc.		individuals or businesses.	
Pusdafil OJK	Created by OJK for fintech lending. Specifically designed for fintech lending with a different tenor than traditional banks.	Data structure similar to SLIK.	Fintech P2P lending providers	Fintech lending institutions are mandated to submit information on current borrowers and ongoing credit to OJK. The database is updated monthly.
Fintech Data Center AFPI	Data used by members of AFPI for risk assessment purposes e.g. recalculating the risk of potential borrowers.	Data includes borrower payment status, write-offs, restructurings.	Accessible to AFPI members only.	Receives historical credit data from AFPI members. Data updated daily.

The limitation of traditional credit scoring methods

The traditional scoring method generates credit scores for those with bank accounts, credit card history, or who have borrowed formal loans before. Therefore, this method limits access to potential borrowers who have never previously taken loans from banks. Compared to larger enterprises, MSMEs are more likely to face such constraints because they have limited access to traditional funding sources, and therefore will not be listed in SLIK (IIX Global 2024).

As an illustration, Amarta, a microfinance marketplace for women microentrepreneurs in rural areas, faced challenges in evaluating the credit risk of their target segment. Rural residents are less likely to have SLIK records because they tend to have limited interaction with traditional banking systems, and are less involved in financial activities such as banking, borrowing, insurance, or investment, compared to urban residents.⁵ **Traditional banks often require collateral for lending due to the increased credit risk associated with the unavailability of credit history.**

⁵ Amarta, interview by Rizka Diandra Firdaus and Maria Sarah, 26 April 2024.

The inability to use existing databases to assess MSMEs' risk, compounded by having limited bank branches and personnel, creates high operational and administrative costs that prevent banks from reaching out to MSMEs, especially those in remote and undigitized areas. Without credit scores, banks would need to conduct field surveys to assess the business, verify its existence, and conduct risk assessments. Apart from Bank Rakyat Indonesia (BRI), which uses field agents to conduct risk assessments, many traditional banks often do not have the capacity and infrastructure to do it.

The lack of traditional credit scores is exacerbated by lenders' limited understanding of certain MSME sectors. For instance, the fishery sector contributes significantly to Indonesia's economy, with an export value of US\$2.71 billion and providing jobs to around 2.7 million workers, with the majority of them being small-scale operators as of 2023 (Gokkon 2023; Windonesia 2024). However, the majority of fish and shrimp fishers struggle to access credit because banks often don't understand aquaculture practices and the risks involved (Asian Development Bank n.d.) Consequently, as of 2024, only 0.28 percent of total bank loans are channeled into the fisheries sector (OJK 2024a).

Similarly, farmers also have limited access to financial capital, with 6.88 percent of total bank credit going into the agriculture sector (OJK 2024a). Many lenders require collateral, which is a challenge for smallholder farmers who often lack formal land titles (East Ventures 2022). Additionally, agricultural production faces unique challenges, like the delay between investment and profit, as well as weather-related risks affecting yields, making borrowing and repayment more difficult for farmers (East Ventures 2022). Consequently, standard loan terms with monthly repayments may not be suitable for farmers. These challenges also make lending to the agriculture sector riskier compared to other sectors that have more predictable business cycles.

Overall, although traditional credit scoring is widely used, it often prevents banks from offering loans to MSMEs with no prior borrowing history, thereby limiting access to potential clients who have not yet engaged with formal financial accounts.

SECTION 2: PROMISING INNOVATION: INNOVATIVE CREDIT SCORING

2.1 OVERVIEW

Generating a credit score can be challenging without a credit history. Worldwide, innovative credit scoring firms are using a wider range of alternative data – such as mobile phone usage, e-commerce activity, social media, and household bill payments – along with machine learning algorithms to assess credit risk (World Bank 2019). These algorithms can identify patterns that can be useful in making credit risk assessments that traditional credit score models may overlook.

J-PAL SEA engaged with key stakeholders in the industry to understand the development of ICS in Indonesia between February to September 2024. This included engaging with ICS platforms like AIForesee and Eureka AI, ICS users such as Amarthia, and KoinWorks, as well as industry experts, including AFPI and Skorlife. The objective was to understand the mechanisms and performance of ICS, identify challenges and opportunities, and explore how research can support ICS development and its use for MSMEs.

2.2 IMPLEMENTING ICS

In Indonesia, ICS is either produced by an ICS platform that creates credit scoring algorithms and offers services to users, such as financial institutions; or generated internally by lending institutions that develop their own algorithms. ICS uses alternative data and is generated using AI/machine learning algorithms or standard statistical methods (see Table 2).

TABLE 2. INNOVATIVE APPROACHES TO CREDIT SCORING

ICS PLATFORMS	ICS USERS
<ul style="list-style-type: none"> Develop a machine learning algorithm to generate credit risk assessment Sources data from third parties as they are not data owners Provide service to financial institutions <p>E.g. Credolab, Eureka AI, AIForesee, Bangun Percaya Sosial</p>	<ul style="list-style-type: none"> Use alternative data to evaluate credit risk Sources data from third-party or in-house Uses AI/non-AI credit scoring system <p>E.g. Amarthia, OVO Finansial</p>

The end-to-end process of ICS

The following is an end-to-end process of how ICS is implemented and used, from data collection, and analysis, to monitoring and evaluation⁶.

1. **Data collection:** ICS platforms first need to decide on the data to feed into the scoring algorithm to assess a person's ability to repay and predict creditworthiness. This data typically includes historical credit applications or alternative data such as digital activity, and mobile usage. When a new variable is integrated into a model, it must undergo an observation period from six to twelve months to test its predictive power. For example, to see whether a person's device type can indicate creditworthiness, an ICS operator would need to have data on loan repayments of people with different devices (which they could acquire from a lending institution) to identify the correlation between the new variable (e.g. device types) and credit risk.
2. **Data analysis:** After the data is collected, the data is placed into the credit scoring model for analysis. then generates a credit risk assessment for the potential borrower.
3. **Monitoring and evaluation:** After the credit score is generated, financial institutions use it to make lending decisions. After loans are repaid, financial institutions can evaluate the effectiveness of the algorithm in improving lending quality. The model is continuously evaluated to ensure its reliability and accuracy over time.

Alternative data types

Different types of alternative data can be used to predict creditworthiness (see Table 3). Long-term behavioral data, such as the payment history of utilities, tends to yield higher predictive accuracy because it sheds more light on the borrowers' past payment behavior. Data types that can provide insight into a person's ability to pay can also be valuable, especially when lenders face difficulty in verifying the income of potential borrowers. For instance, the frequency of phone credit top-ups, can serve as a proxy for financial stability, and e-commerce transactions can be used to assess a business's risk level based on its revenue and sales information. Table 3 provides examples of the types of alternative data and its use in credit scoring.⁷

Data points are harvested from any internet-connected platform, including phones, tablets, computers, and other devices, and can be either sourced internally or from third parties by building partnerships with them.⁸

⁶AIForesee, interview by Rizka Diandra Firdaus and Maria Sarah, 19 March 2024.

⁷The types of data that can be used for ICS were gathered through stakeholder interviews with several ICS platforms and users.

⁸AIForesee, interview by Rizka Diandra Firdaus and Maria Sarah, 19 March 2024.

TABLE 3. TYPES OF ALTERNATIVE DATA

DATA TYPE	CREDIT SCORING APPLICATION
Tax history	NPWP Status
Utilities	Bill payments (electricity, water)
Mobile phone	Types of applications downloaded e.g. gambling, e-commerce, banks, financial applications, device type, communication behavior (the frequency of calls, messages)
Social media	Social network
E-commerce transactions	Shop revenue on e-commerce, merchants' income, merchants' activity, average spending
E-procurement	Buying goods
Geographical information	Weather information, risk profile
Telecommunications data	Monthly top-up packages, upgrades, plans (prepaid vs postpaid), phone activity time
Interaction	Interactions between users and entities, such as cell towers, locations, or websites
Sector-specific data	Harvest results, livestock survival, and mortality rates

While these data are useful to measure credit risk, based on our office’s engagements with ICS platforms, collecting these types of data can be challenging because the platforms that own the data are often reluctant to share it. They are worried about how the data will be used, potential competition, the risk of losing users to other platforms, and have a lack of understanding of the methods to share data safely (i.e. protecting personal information), raising data privacy concerns.⁹ Additionally, some data owners may already have existing partnerships with financial institutions within their ecosystems, which could limit their ability to collaborate with competing companies. For example, while the Gojek platform may have valuable e-commerce transaction data for alternative credit scoring, it is closely linked to its common shareholders, including Kredit Pintar and Bank Jago. Similarly, comparable proprietary data owned by Grab is used for its respective lending products and not shared with competing platforms and banks.

⁹AIForesee, interview by Rizka Diandra Firdaus and Maria Sarah, 19 March 2024.

2.3 THE OPPORTUNITIES OF USING ICS

Our office's literature review and stakeholder engagements reveal that various benefits arise from the use of alternative data and machine learning. Discussions with ICS users highlighted that ICS can increase financial inclusion for entrepreneurs with limited credit, streamline data collection, verification processes, and enhance visibility into credit risk to lower screening costs while mitigating fraud risk.

1. Expand financial access to entrepreneurs that were previously deemed unbankable.

ICS can provide a credit score for those who do not have a traditional credit history through its use of non-traditional data (such as digital footprints from mobile data) to generate the scores.

For instance, as discussed in [Section 1.3](#), shrimp and fish farmers often encounter difficulties in borrowing from traditional banks due to their limited credit history and banks' hesitancy to lend to sectors where they have limited expertise. Sector-specific data can help banks mitigate the risks associated with lending to these MSMEs. Sector-specific data can typically be acquired through collaboration with third-party organizations, such as microfinance institutions, aquatech, and agritech startups like Amartha, Jala, and Chikin. Their connections with MSME communities in specific sectors, such as the fisheries and agriculture sector, allow them to provide insights into MSMEs' business processes and give inputs on alternative indicators that can help banks conduct a more comprehensive assessment of credit risk, beyond traditional credit history (see Case Study 1).

Case Study 1: Partnering with third-party organizations to reach MSMEs

Jala is an Indonesia-based aquatech startup that provides shrimp farmers with real-time, data-driven solutions to enhance their farming productivity (The Fish Site 2023). Its digital platform enables farmers to track and analyze shrimp farming conditions, helping them to make better decisions and improve yields (The Fish Site 2023). They also offer other services including marketplace access for harvest sales and a credit scoring service to enable farmers to prove creditworthiness and gain access to affordable financing options (The Fish Site 2023).

While fish and shrimp farmers require credit, financial institutions often view lending to the fisheries sector as risky. Institutions like Jala that have a deep understanding of the aquaculture industry and shrimp farmers can complement financial institutions' credit risk assessments by providing sector-specific indicators such as farm performance, production levels, and disease patterns (The Fish Site 2023). This data not only improves risk assessment but also enables banks to develop tailored credit products that meet the unique needs of shrimp farmers.

Partnering with third-party organizations with strong ties to MSME communities can mitigate risks and shift the perception that lending to MSMEs is inherently risky.

ICS can also improve credit risk assessment by providing additional data points to assess creditworthiness. For individuals without a prior borrowing history, alternative data like e-commerce spending patterns can be used to establish a credit score, enabling financial institutions to assess their risk level.

Additionally, ICS can also help banks reach individuals who have borrowed before but fall into the medium-risk category. In this memo, medium-risk borrowers are defined as those with a credit history but have credit scores that are not as favorable as those in the low-risk category. Factors contributing to a medium-risk score include missed or late payments, a limited number of credit accounts, high credit utilization, or a shorter credit history (Dieker and Thomas 2024). Other reasons might include banks encountering difficulties in verifying an individual's income status or residency in remote areas, where financial data is harder to verify.¹⁰

In Indonesia, the percentages of adults registered in the official credit registry and the credit bureau as of 2020 are both at low levels (40 percent and 31 percent, respectively) (Indonesia Business Council 2024). Our stakeholder engagements suggest that many of them fall into the medium-risk category.¹¹ Borrowers in this category often face challenges such as not qualifying for the best loans or being subjected to higher interest rates, as lenders view them as riskier compared to those in the low-risk category.¹²

The factors influencing an individual's credit score vary, and understanding the underlying causes requires a review of their credit report. However, alternative digital data sources may provide valuable insights that can help banks better assess risk and potentially reclassify borrowers. For instance, if income verification is the primary issue, data such as phone credit top-up patterns could be a proxy for financial stability, offering a clearer picture of the borrowers' capacity to pay.

Studies from around the world have used machine learning models to evaluate the effectiveness of using alternative data sources, such as digital and mobile footprints, in predicting loan outcomes (Berg et al. 2019; Agarwal et al. 2023; Björkegren and Grissen 2019). Overall, they found that alternative data can enhance credit assessment and potentially expand approval for loans to more customers, especially those with no credit score or lower income and education levels. For example, Agarwal et al. (2023) showed via machine learning that a credit risk model that uses mobile and social footprint (e.g., types of apps installed, presence of social apps, number of contacts) improves on models that only use standard credit bureau information and customer characteristics. They also show that the presence of a financial app (e.g. mobile banking, stock trading apps) can signal financial sophistication, making it a valuable variable for predicting creditworthiness.

¹⁰Skorlife, interview by Rizka Diandra Firdaus and Maria Sarah, 4 September 2024.

¹¹Ibid.

¹²Ibid.

Overall, early studies using machine learning models have shown that using alternative data can expand credit to individuals who have never borrowed before. However, research remains limited, focusing primarily on its effectiveness for consumption loans. Additionally, no randomized evaluations have assessed the impact of alternative data on loan decisions. These are questions that require further exploration using randomized evaluations.

Future research areas

- Does the inclusion of alternative data improve the accuracy of predicting repayment rates and reduce default rates?
- How effective is alternative data in assessing the creditworthiness of borrowers seeking productive loans (e.g., small business loans) compared to consumption loans?
- Can data such as e-commerce revenue or platform activity accurately predict repayment capacity for entrepreneurs?

2. Machine learning can improve decision-making and reduce screening costs by increasing visibility into applicants' credit risk while mitigating fraud risk.

Several studies have also found that alternative targeting methods, such as using machine learning, can enhance loan officers' lending choices. In a randomized evaluation, Bryan et al. (2023) found that loan officers may not accurately assess potential clients, leading to suboptimal lending choices. In the study, loan officers incorrectly perceived clients predicted by machine learning as top performers to be more likely to default than those predicted as low performers. Loan officers selected their clients based on their previous performance with smaller loans, assuming that those who did well would also do well with larger loans. However, these clients tended to be risk-takers and did not perform well with larger loan amounts. Researchers suggest that loan officers may have been making inefficient choices when selecting clients due to a lack of effective targeting methods. It suggests that lending institutions could improve their client selection process by implementing better targeting techniques, such as the machine learning algorithm, and using additional psychometric data. See the J-PAL brief summarizing this work [here](#).

In another randomized evaluation, Chen et al. (2023) evaluated whether providing photos of prospective borrowers (aka facial information) could improve loan approval decisions. The study found that machine learning models using facial information outperformed humans in predicting prepayment behaviours as humans have biases and overly rely on the wrong parts of facial information in their decision-making. For example, subjects gave higher scores to borrowers who had facial features like themselves, were more beautiful, and dressed formally but these did not have predictive power on repayment behavior.

While reducing screening costs, using ICS can also enhance fraud detection by leveraging alternative data. For instance, alternative data, such as cell phone bills, can enable financial institutions to identify potentially fraudulent businesses; such as potential misrepresentations from applicants who claim to own a business in one location but are primarily active in another.¹³

Overall, previous randomized evaluations have shown that using alternative data and machine learning can improve credit decisions, but the evidence is still limited and mixed, with effectiveness depending on the data being used. Additionally, the costs and benefits of using ICS are also not fully understood. Therefore, we scope several questions that can potentially assist in informing the future design and regulations surrounding ICS.

Future research areas

- How can financial service providers effectively integrate the assessment of ICS with those made by loan officers?
- Is the predictive accuracy of machine learning higher compared to that of loan officers?
- Is using machine learning more cost-effective than employing loan officers? How can ICS and human judgments be effectively combined?

SECTION 3: KEY POINTS FOR CONSIDERATION

While the use of alternative data and machine learning is promising, there are also important considerations when applying it for credit scoring.

- 1. The use of alternative data may need to be complemented with traditional credit and financial information, and tailored based on the target segment.**

Several studies using machine learning models, including those by Berg et al. (2019) and Agarwal et al. (2023), found that mobile and social footprints can predict default. However, they work best when combined with credit bureau scores and detailed financial information about customers' income and expenses. The distinct insights into financial behavior from each data type enhance the credit model's discriminatory power.

ICS providers emphasize the importance of selecting alternative variables that align with the target segment. For instance, low-income households, particularly in remote areas, often have low digital literacy and lack the necessary digital footprint for accurate credit scoring. In such cases, field visits

¹³ Eureka AI, interview by Rizka Diandra Firdaus and Maria Sarah, 18 April 2024.

by credit officers are crucial for collecting information on living conditions, household size, business performance, and other relevant insights that can be used as an indicator of creditworthiness.

Certain consumer behaviors, such as frequent changing of SIM cards or phone sharing, can complicate the use of alternative data in generating reliable credit scores.¹⁴ For example, Amarta, a financial services company catering to women microentrepreneurs in rural areas experimented with using cell phone bills and e-commerce data to evaluate creditworthiness and found that it does not reveal repayment ability. In rural areas, long-term phone number usage is uncommon, so cell phone bills do not often reveal long-term behavior. Similarly, analyzing average e-commerce income fails to measure credit risk, as only a small percentage of Indonesians in rural areas have stores in e-commerce. If the microentrepreneurs being targeted are in the agriculture sector, an example of a more useful indicator is geographical data which may include weather patterns and agricultural risk profiles.

This underscores the need to tailor credit scoring models to the specific characteristics of each segment. In areas with limited digitalization, alternative data may be less informative, and a community-based lending model that leverages local information could offer a more accurate assessment of creditworthiness. Overall, the limited research on the predictive power of different types of alternative data and their use across demographics presents an opportunity to explore whether it should complement traditional data and its effectiveness in assessing credit risk for entrepreneurs from diverse socioeconomic backgrounds.

Future research areas

- How does the predictive power of digital footprints compare to that of traditional financial metrics across different demographics?
- Are certain types of alternative data more predictive for specific borrower profiles?
- Which combinations of traditional and alternative data are effective for credit risk assessment?
- Which types of alternative data are most effective for assessing the creditworthiness of entrepreneurs from varying socioeconomic backgrounds?

2. A balance must be struck to ensure data privacy while allowing ICS to acquire sufficient, high-quality individualized data to accurately measure credit risk.

ICS offers significant advantages for financial institutions in reaching individuals who were previously excluded from traditional banking services. To measure credit risk accurately, ICS needs to feed quality and sufficient individualized data of the borrower into the algorithm. However, as

¹⁴Amartha, interview by Rizka Diandra Firdaus and Maria Sarah, 26 April 2024.

discussed in [Section 2](#), there are several challenges that hinder optimal data collection and usage, including data owners' hesitancy to share data, and their lack of understanding about the appropriate safe data-sharing method to protect personal information. There is also no standardized data collection protocol among firms. Hesitancy to share data often arises when national regulations clash with internal policies. For example, while the [Personal Data Protection Law](#) mandates financial institutions to share data upon individual requests, internal policy may forbid such practices.

To clarify data-sharing protocols, facilitate data standardization, and promote safe AI use, the government of Indonesia is creating an integrated MSME database, enacted the [Personal Data Protection Law](#), and issued ethical AI use guidelines, including the Ministry of Communication and Informatics' [Circular Letter No. 9 of 2023](#) and OJK's [Ethical Guidelines on Responsible and Trustworthy AI](#) (Antara News 2024a; Indonesia.go.id 2024; Prasetyo 2024; Menteri Komunikasi dan Informatika Republik Indonesia 2023; OJK 2024c). Additionally, efforts have been made to strengthen data protection through the [Indonesian Law No.19 of 2016](#) on Electronic Information and Transactions which includes the right to be forgotten clause, allowing individuals to request the removal of personal information from online platforms (BPK 2016). More recently, OJK has also issued [OJK Regulation No.3/2024](#) to support financial technology innovations, whilst ensuring consumer and data protection (OJK 2024d).

Given the extensive data that ICS collects, consumer privacy is important. However, since ICS requires alternative data sources for its function, the government must take a proactive role in balancing the operation of ICS and the safeguarding of personal data. Policies and regulations to encourage safe data sharing and storage and fostering a supportive policy framework for ICS can help the government achieve this balance. Moving forward, while ICS brings many benefits, implementing effective data protection measures and creating a framework for security accountability is needed to ensure that data remains secure and gain user trust.

3. Credit scoring algorithms can lead to or perpetuate discrimination against marginalized groups

Discrimination can occur when certain groups are favored and given advantages, such as being offered credit, while other groups are systematically disadvantaged, such as by being denied credit. It can be based on several dimensions, including race, religion, language, gender, nationality, age, sexual orientation, and others (Kelly and Mirpourian 2021). Certain variables are used as inputs to credit scoring algorithms can lead to or perpetuate discriminatory practices. Examples of these variables and the biases that may arise are the following:

- **Sampling bias:** This can arise when one population is either disproportionately included or excluded in a training dataset. For example, if smartphone usage is used to assess credit risk in areas where women are less likely than men to own smartphones, bias may occur as the algorithm will depend more on data from men than from women (Wijaya 2023).

- **Labeling bias:** This can occur based on how the data is labeled and categorized to make the data more easily understood and used by an algorithm. For instance, if utility bills are used to measure credit risk, women may receive lower scores since bills are often registered under men as the household head, potentially resulting in higher scores for men (Wijaya 2023).
- **Outcome proxy bias:** This can occur when a machine learning assignment is not clearly defined. For instance, using residential addresses as a proxy for credit default prediction can introduce bias, as default rates may be higher in lower-income areas, but this doesn't imply that a specific individual will default (Wijaya 2023).

While limited, there is research that finds that including certain variables can perpetuate existing discriminatory practices. For example, a randomized evaluation by Kisat (2021) examined how loan officers and machine learning algorithms responded when demographic information of loan applicants was revealed in Pakistan. Revealing demographic information to loan officers decreased discrimination, as loan officers may have aimed to minimize disparities in credit access between genders. When the same information was revealed to an algorithm, discrimination increased and the algorithm reduced default by 3-7 percent compared to when the algorithm did not use demographic information.

More research is needed to understand the discriminatory risks in credit scoring, especially in countries where data collection and standardization is a challenge, like in Indonesia.

Future research areas

- How do the credit decisions of machine learning algorithms compare with those made by loan officers when evaluating borrowers from diverse demographic profiles?
- What are the most effective strategies for mitigating discriminatory risks in machine learning-based credit scoring models?
- Could combining machine learning models with loan officer decisions improve fairness and accuracy in credit assessments?

4. ICS can expand financial access to the unbanked population but may increase risk by extending credit to financially inexperienced borrowers.

The development of fintech products and services has been critical in reducing poverty by increasing access to financial products and services for poor and low-income families. However, this progress has not been matched by the necessary level of financial literacy needed to responsibly use these products and services. The 2024 National Financial Literacy and Inclusion Survey shows a gap between financial literacy and inclusion in Indonesia (OJK 2024b). While 65.43 percent of those surveyed demonstrate an understanding of financial products and services, 75.02 percent have access to them, indicating that financial access outpaces financial knowledge (OJK 2024b). This suggests that while many Indonesians can access financial services but may lack the knowledge to use them

effectively. Fintech P2P lending providers also resonate with this concern, highlighting that most MSMEs struggle to distinguish between legal and illegal lending platforms, understand their financing needs, determine appropriate borrowing amounts, and recognize that credit must be repaid.¹⁵ They also lack the awareness that failure to repay will be permanently recorded in credit databases like Pusdafil, making future borrowing more difficult.¹⁶ Therefore, increasing credit access needs to be complemented with financial literacy training to ensure that borrowers have sufficient knowledge and skills to borrow responsibly for their business growth.

Despite its potential to expand financial access to underbanked communities, there is a concern that it may increase risk by extending credit to financially inexperienced individuals with low financial literacy. As more financial products and services become available, improving financial literacy is crucial to ensure responsible borrowing. Further studies can help the government and financial institutions understand how to improve consumers' financial literacy effectively. Additionally, research can explore strategies to raise MSME owners' awareness about ICS, enabling them to dispute unfavorable credit decisions and take corrective actions.

CONCLUSION

The challenge of accessing finance remains a significant barrier to MSME growth. The low borrowing rates among these businesses are primarily due to complex application procedures and requirements that MSMEs struggle to meet and banks' reluctance to lend to MSMEs due to their absence from the credit registry, raising the risks and costs of serving them. Despite the mandate for banks to allocate 30 percent of their total credit to MSMEs, these challenges often hinder them from meeting this target (BPK 2021).

Leveraging ICS presents a promising solution. ICS can lower the costs of serving MSMEs and encourage banks to lend more by enabling better credit risk measurement. A best practice observed on the ground is the partnership between lending institutions and ICS platforms. For example, rather than directly collecting alternative data themselves, financing institutions can collaborate with organizations like Jala, which have sector-specific expertise. These organizations can conduct credit risk assessments using sector-specific alternative data that complements traditional credit scoring methods.

Moreover, the use of alternative data requires flexibility. While digital data from mobile phones and online platforms can be useful, areas with limited digitalization may need to rely on other types of

¹⁵“Fintech Talk bersama JULO “#BISATERUS Membangun Kekuatan UMKM Melalui Literasi Keuangan dan Kredit Digital,” panel discussion, Jakarta, June 14 2024.

¹⁶Ibid.

data. Community-based lending model, which leverages local information could also provide a more accurate assessment of creditworthiness. This opens opportunities for further research to identify alternative data sources for populations that remain under-digitized.

While ICS has potential, it also raises concerns about bias in credit assessments and data privacy. Further research is needed to understand the potential bias of using ICS and identify effective strategies to overcome it. As consumer data is also used in ICS, the government can also take a proactive role in striking a balance between enabling the operation of ICS and safeguarding consumers' data. Strengthening policies and regulations around data sharing, storage, and security will be critical to fostering trust in ICS systems. As the availability of financial products grows, improving financial literacy is crucial to ensure responsible borrowing. More research is needed to help governments and financial institutions understand how to improve consumers' financial literacy effectively, particularly among MSME owners.

Taken together, while ICS is a promising tool for expanding financial inclusion to previously unbanked entrepreneurs, it must be implemented carefully. Moving forward, further research can help guide the development and use of algorithms that can safely use alternative data to boost financial access for MSMEs and minimize biases.

REFERENCES

AFPI. 2023. "Pendanaan Dari Fintech Lending Naikkan Omzet UMKM." AFPI, November 21, 2023. <https://afpi.or.id/articles/detail/pendanaan-dari-fintech-lending-naikkan-omzet-umkm.da>

Agarwal, Sumit, Shashwat Alok, Pulak Ghosh, and Sudip Gupta. 2023. "Financial Inclusion and Alternate Credit Scoring: Role of Big Data and Machine Learning in Fintech." *Indian School of Business*,

Antara News. 2024a. "Ministry continues to collect cooperative, MSME data." March 26, 2024. <https://en.antaraneews.com/news/309318/ministry-continues-to-collect-cooperative-msme-data>.

Antara News. 2024b. "Kemenkop UKM Sebut Skema Credit Scoring KUR Dapat Turunkan Gagal Bayar hingga 4 Persen." January 19, 2024. <https://www.antaraneews.com/berita/3923496/kemenkopukm-credit-scoring-turunkan-gagal-bayar-hingga-4-persen>

Asian Development Bank. n.d. "Sector Assessment (Summary): Agriculture, natural resources, and rural development - Fisheries [shrimp aquaculture]." <https://www.adb.org/sites/default/files/linked-documents/55020-001-ssa.pdf>

Badan Pusat Statistik. 2024. "Profil Industri Mikro dan Kecil." Profil Industri Mikro dan Kecil 2023. <https://www.bps.go.id/id/publication/2024/09/18/52d85cbe9de005b6f5d69f95/profil-industri-mikro-dan-kecil-2023.html>.

BPK. 2016. "Perubahan Atas Undang-Undang Nomor 11 Tahun 2008 Tentang Informasi Dan Transaksi Elektronik." <https://peraturan.bpk.go.id/Details/37582/uu-no-19-tahun-2016>.

BPK. 2021. "Peraturan Bank Indonesia Nomor 23/13/PBI/2021 tentang Rasio Pembiayaan Inklusif Makroprudensial bagi Bank Umum Konvensional, Bank Umum Syariah, dan Unit Usaha Syariah." <https://peraturan.bpk.go.id/Details/219376/peraturan-bi-no-2313pbi2021>.

Berg, Tobias, Valentin Burg, Ana Gombović, and Manju Puri. 2019. “On the Rise of FinTechs: Credit Scoring Using Digital Footprints.” *The Review of Financial Studies* 33, no. 7 (September): 2845-2897. <https://doi.org/10.1093/rfs/hhz099>.

Björkegren, Daniel, and Darrell Grissen. 2019. “Behavior Revealed in Mobile Phone Usage Predicts Credit Repayment.” *The World Bank Economic Review* 34, no. 3 (November): 618-638.

Bryan, Gharad T., Dean Karlan, and Adam Osman. 2023. “Big Loans to Small Businesses: Predicting Winners and Losers in an Entrepreneurial Lending Experiment.” *National Bureau of Economic Research*, (November). 10.3386/w29311.

Cai, Jing, Arya Gaduh, Mochamad T. Akbar, Aulia Larasati, Erysa A. Poetry, and Maria V. Sarah. 2024. “Building Pathways to Support Micro, Small, and Medium Enterprise Growth.” <https://www.povertyactionlab.org/review-paper/building-pathways-support-micro-small-and-medium-enterprise-growth>.

Chen, Zeyang, Yu-Jane Liu, Juanjuang Meng, and Zeng Wang. 2023. “What’s in a Face? An Experiment on Facial Information and Loan-Approval Decision.” *Management Science* 69 (4): 2263-2283. <http://dx.doi.org/10.1287/mnsc.2022.4436>.

Dieker, Nicole, and Seychelle Thomas. 2024. “What Is Considered A Fair Credit Score?” Bankrate. <https://www.bankrate.com/personal-finance/credit/what-is-fair-credit-score/>.

East Ventures. 2022. “The role of fintech lending to Indonesia's agribusiness sector.” East Ventures. <https://east.vc/news/insights/the-role-of-fintech-lending-to-indonesias-agribusiness-sector/>.

Gokkon, Basten. 2023. “Rule change sees foreign investors back in Indonesia's fisheries scene.” *Mongabay*, March 10, 2023. <https://news.mongabay.com/2023/03/indonesia-fisheries-management-policy-foreign-investment-marine-sustainable/>.

IIX Global. 2024. “Ford Feasibility Study for an Indonesian Orange Bond.” <https://iixglobal.com/ford-feasibility-study-download/>.

Indonesia.go.id. 2024. “Era Baru Perlindungan Data Pribadi.” October 26, 2024.

<https://indonesia.go.id/kategori/editorial/8725/era-baru-pelindungan-data-pribadi?lang=1>

International Finance Corporation. 2016. “Women-owned SMEs in Indonesia: A Golden Opportunity for Local Financial Institutions.” International Finance Corporation.

<https://documents1.worldbank.org/curated/zh/691661477568338609/pdf/109534-WP-ENGLISH-SME-Indonesia-Final-Eng-PUBLIC.pdf>

International Finance Corporation. 2024. “IFC's Landmark Investment to Ramp Up Sustainable Finance in Indonesia, Boost Resilience.” International Finance Corporation.

<https://www.ifc.org/en/pressroom/2024/ifc-s-landmark-investment-to-ramp-up-sustainable-finance-in->

[in-](https://www.ifc.org/en/pressroom/2024/ifc-s-landmark-investment-to-ramp-up-sustainable-finance-in-)

[indo#:~:text=IFC%20is%20committed%20to%20supporting,funds%20mobilized\)%20exceeding%20%](https://www.ifc.org/en/pressroom/2024/ifc-s-landmark-investment-to-ramp-up-sustainable-finance-in-)

[2410%20billion.](https://www.ifc.org/en/pressroom/2024/ifc-s-landmark-investment-to-ramp-up-sustainable-finance-in-)

International Labor Organization. 2019. “Financing Small Businesses in Indonesia: Challenges and Opportunities.” Jakarta: International Labour Organization.

<https://www.ilo.org/publications/financing-small-businesses-indonesia-challenges-and-opportunities>

Kelly, Sonja, and Mehrdad Mirpourian. 2021. “Algorithmic Bias, Financial Inclusion, and Gender.” [https://www.womensworldbanking.org/wp-](https://www.womensworldbanking.org/wp-content/uploads/2021/02/2021_Algorithmic_Bias_Report.pdf)

[content/uploads/2021/02/2021_Algorithmic_Bias_Report.pdf](https://www.womensworldbanking.org/wp-content/uploads/2021/02/2021_Algorithmic_Bias_Report.pdf).

Kisat, Faizaan. 2021. “Loan Officers, Algorithms, & Credit Outcomes: Experimental Evidence from Pakistan.” (November). https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3956251.

Kristanus, Arnoldus. 2023. “MSMEs Account for 97% of Job Opportunities in Indonesia.” Jakarta Globe. <https://jakartaglobe.id/business/msmes-account-for-97-of-job-opportunities-in-indonesia>.

Menteri Komunikasi dan Informatika Republik Indonesia. 2023. “Surat Edaran Menteri Komunikasi dan Informatika Nomor 9 Tahun 2023 tentang Etika Kecerdasan Artifisial.”

https://jdih.kominfo.go.id/produk_hukum/view/id/883/t/surat+edaran+menteri+komunikasi+dan+informatika+nomor+9+tahun+2023

OJK 2024a. “Laporan Surveillance Perbankan Indonesia - Triwulan II 2024.”

<https://ojk.go.id/id/kanal/perbankan/data-dan-statistik/laporan-profil-industri-perbankan/Pages/Laporan-Surveillance-Perbankan-Indonesia---Triwulan-II-2024.aspx>

OJK. 2024b. “Joint Press Release: OJK And Statistics Indonesia Present National Survey On Financial Literacy And Inclusion 2024 Findings.” August 2 2024. <https://ojk.go.id/en/berita-dan-kegiatan/siaran-pers/Pages/OJK-And-Statistics-Indonesia-Present-National-Survey-On-Financial-Literacy-And-Inclusion-2024-Findings.aspx#:~:text=SNLIK%202024%20findings%20showed%20that,financial%20literacy%20and%20inclusion%20rate>.

OJK. 2024c. “Panduan Kode Etik Kecerdasan Buatan (Artificial Intelligence/AI) yang Bertanggung Jawab dan Terpercaya di Industri Teknologi Finansial.” <https://ojk.go.id/id/berita-dan-kegiatan/publikasi/Pages/Panduan-Kode-Etik-Kecerdasan-Buatan-AI-yang-Bertanggung-Jawab-dan-Trustworthy-in-Financial-Tech-Industry.aspx>

OJK. 2024d. “Penyelenggaraan Inovasi Teknologi Sektor Keuangan.” OJK. <https://ojk.go.id/id/regulasi/Pages/POJK-3-2024-Penyelenggaraan-Inovasi-Teknologi-Sektor-Kuangan.aspx>.

OJK. 2024e. “Roadmap of Financing Companies Development and Strengthening 2024-2028.” OJK. <https://ojk.go.id/en/berita-dan-kegiatan/info-terkini/Pages/Roadmap-of-Financing-Companies-Development-and-Strengthening-2024-2028.aspx>

Prasetyo, Teguh Adi. 2024. “New AI Regulation in Indonesia Aims to Address Ethical Use and Data Security.” Jakarta Globe. <https://jakartaglobe.id/tech/new-ai-regulation-in-indonesia-aims-to-address-ethical-use-and-data-security#:~:text=These%20guidelines%20include%20ensuring%20that,social%20relationships%2C%20and%20individual%20opinions.>

Purnamasari, Lia, Rizqi Ashfina, Maesy Angelina, Andini Kamayana, Poppy Ismalina, and Pertivi Triwidiahening. 2023. “Indonesia's Women Impact Entrepreneurs: Her Barriers Are More Systemic Than You Think | SEADS.” *ADB Seeds*, January 26, 2023. [https://seads.adb.org/solutions/indonesias-women-impact-entrepreneurs-her-barriers-are-more-systemic-you-think.](https://seads.adb.org/solutions/indonesias-women-impact-entrepreneurs-her-barriers-are-more-systemic-you-think)

Puspadini, Mentari. 2024. “Rasio Kredit UMKM RI Rendah, Menkop UKM Buka Penyebabnya.” *CNBC Indonesia*, March 7, 2024. <https://www.cnbcindonesia.com/market/20240307110414-17-520373/rasio-kredit-umkm-ri-rendah-menkop-ukm-buka-penyebabnya#:~:text=Rasio%20Kredit%20UMKM%20RI%20Rendah%2C%20Menkop%20UKM%20Buka%20Penyebabnya,-Mentari%20Puspadini%2C%20CNBC&text=Utamanya%2C%20mereka%20tidak%20memiliki%20agunan,syarat%20untuk%20meminta%20kredit%20bank.f>

Simanjuntak, Martha H. 2024. “OJK susun aturan untuk tingkatkan pemberdayaan UMKM.” Antara News. <https://www.antaraneews.com/berita/4253883/ojk-susun-aturan-untuk-tingkatkan-pemberdayaan-umkm>

Sutrisno, Eri. 2024. “Jalan Baru OJK: Agar Akses Pembiayaan UMKM Lebih Mudah.” Indonesia.go.id.

<https://indonesia.go.id/kategori/editorial/8630/jalan-baru-ojk-agar-akses-pembiayaan-umkm-lebih-mudah?lang=1>

The Fish Site. 2023. “Jala nets \$13 million investment.”

<https://thefishsite.com/articles/jala-nets-13-million-investment>

60decibels. 2024. “The state of Indonesian Micro and Small Enterprises, 2023/24.”

<http://60decibels.com/wp-content/uploads/2024/06/Mastercard-Striving-to-Thrive-Indonesia-2023-34-1.pdf>.

Wijaya, Trissia. 2023. “The Rise of Innovative Credit Scoring System in Indonesia: Assessing Risks and Policy Challenges.”

<https://repository.cips-indonesia.org/media/publications/560780-the-rise-of-innovative-credit-scoring-sy-0f4556b9.pdf>.

Windonesia. 2024. “Indonesia's Fishery Export Performance in First Half of 2024”

<https://windonesia.com/article/indonesias-fishery-export-performance-in-first-half-of-2024>

World Bank. 2019. “Credit Scoring Approaches Guidelines.”

<https://thedocs.worldbank.org/en/doc/935891585869698451-0130022020/original/CREDITSCORINGAPPROACHESGUIDELINESFINALWEB.pdf>.