Analysis of Regulations and Techno-Economic in the Digital Multifinance Industry

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Abstract. The financial and financing industry, particularly the multifinance sector, is undergoing significant transformations due to digital technology. This research investigates the impact of digital technology on the multi finance industry in Indonesia, focusing on the credit scoring system that addresses challenges related to the approval process and system analysis. The study examines the feasibility of implementing a digital multifinance credit scoring system in Indonesia, especially for prospective borrowers from technical, economic, and regulatory perspectives. The developed credit scoring model using the XGBoost algorithm demonstrates 70% accuracy on training data and 69% on test data, with a precision rate of 75% and a ROC value of 87%. The business feasibility analysis shows promising financial prospects with an NPV of Rp979,247,084, an IRR of 22%, a MIRR of 17%, a Payback Period of 4 year 4 month, and a Profitability Index of 1.09663. These metrics collectively suggest that the project has potential for significant financial benefits in the long term. The research also emphasizes the crucial role of regulations by the Financial Services Authority (OJK), highlighting the need for proper oversight to ensure financial stability, consumer protection, and data security.

Keywords: Digital Technology, Multifinance Industry, credit scoring systems, Regulations.

1 Introduction

Digital technology plays a crucial role in supporting the growth of business, including multifinance companies. It transforms business operations, service delivery, and customer interactions. However, with technological advancements, the challenges for the multifinance industry have become more complex, necessitating competitive strategies to meet market demands. Implementing digital technologies like IoT, AI, and Blockchain can significantly improve operational efficiency, enhance customer service, improve operational risks more effectively [1]-[2]. The financial industry, particularly.

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The financial industry, particularly the financing and lending sector, is rapidly adopting digital technology to meet market needs [1]. Multifinance companies in Indonesia often take several days to approve financing applications, highlighting the need for enhanced digital platforms to expedite this process to just a few minutes [3]. Continuous monitoring and development of financial technology ecosystems are essential to maintain monetary and financial system stability and support economic growth. Multifinance companies in Indonesia leverage various digital technologies, including mobile applications, online services, business process automation, and data analysis to assess credit risk. Security technologies like data encryption and user identification systems are also employed to protect data and reduce fraud. According to the Financial services Authority (OJK) data from March 2024, there ae 146 financing companies in Indonesia, reflecting the industry's growth alongside digital technology advancement, cybersecurity, operational resilience, consumer protection, and data security. Proper data governance and compliance with relevant laws are vital, as data is essential for lending, fraud prevention, and consume growth [2]-[4].

This research analyzes the digital platforms used by major multifinance companies in Indonesia, aiming to recommend updated system models based on technological, regulatory, and economic aspects. Previous studies show that integrating data from financial-technology lending and multifinance companies significantly impacts credit risk models. The study will provide a digital system solution to expedite the credit approval process, enhancing efficiency and effectiveness in meeting public needs.

The expected outcome is a comprehensive technological, economic, and regulatory analysis, including cost design and regulatory compliance for digital system and credit scoring.

2 Basic Concepts

2.1 Multifinance Industry

The multifinance industry has rapidly evolved with the integration of digital technology. Multifinance companies offer a variety of financial services such as loans, leasing, and credit [5]. Digital technology has made these services more accessible and efficient. It enhances operational efficiency and financial service offerings. Multifinance increases financial access and supports the growth of SMEs, significantly contributing to the national economy [6].

2.2 Digital Integration in the Multifinance Credit Scoring

The integration of digital technologies in the multifinance industry has led to significant changes, particularly in credit scoring systems. On the other hand, credit scoring models based on machine learning provide more accurate predictions by analyzing larger and more complex datasets [7].

Successful adoption of these technologies is crucial for competitiveness in the digital

era. The digital transformation also includes developing mobile applications to facilitate online financing transactions, automating business processes, and integrating digital platforms, enhancing usability and market potential, particularly in financial services [8]-[9].

Credit scoring is a crucial aspect of the multifinance industry, determining the creditworthiness of potential borrowers. Traditional credit scoring models are being replaced by machine learning models that provide more accurate predictions by analyzing large datasets and identifying patterns. Credit scoring systems utilize various data sources, including financial information and transactions, to assess customer creditworthiness, combining internal and external data for informed decisions. These models categorize consumer credit applications into good or bad risk groups, using statistical methods to predict outcomes and manage credit risk [10]-[11].

2.3 Economic Aspect

Economic analysis in the multifinance industry involves evaluating the costs and benefits of implementing digital technologies. This includes analyzing CAPEX, OPEX [12], and conducting business feasibility analysis. When evaluating business feasibility, key financial metrics typically considered include Net Present Value (NPV), Internal Rate of Return (IRR), Payback Period (PP), and Profitability Index (PI). These metric are crucial for assessing the potential profitability and viability of a business venture [13].

2.4 Regulations

The digital finance industry is rapidly growing, with regulators balancing appropriate regulatory environments and market safety [14]. In Indonesia, the Financial Services Authority (OJK) oversees the digital multifinance industry under Law Number 7/POJK.05/2022 OJK regulations [15], especially regarding credit scoring systems, support the industry's growth and stability [16]. Internationally, harmonizing financial regulations fosters global financial stability [14].

Domestically, the OJK aims to create a healthy business climate and protect stakeholders, with the authority to enhance financial sector stability [16]. Compliance with OJK regulations improves credibility and customer trust in the multifinance sector. Bank Indonesia regulation No.20/8/PBI/2018 provides guidelines for financial agreements [17].

The information and Electronic Transactions Law Number 1 of 2024 (UU ITE) protects system use and customer data in digital multifinance , forming a crucial legal framework [18]. Law No.27 of 2022 emphasizes personal data protection as a fundamental right, providing a comprehensive legal framework to safeguard personal data [19].

3 Research Methodology

The research involves developing a system model for digital multifinance credit scoring application and analyzing different scenarios to evaluate its performance.

3.1 Research Approach

The research methodology for developing a credit scoring system in the digital multifinance sector involves a structured approach comprising several key stages. Initially, the research process begins with gathering essential information and data necessary to support the study. This is followed by a technical analysis that delves into the technical aspects of digital multifinance systems, examining the models used and the system structure based on the collected data. Subsequently, an economic analysis, expenditures over a specified period for the systems or programs under study. Additionally, a regulation analysis ensures the system's compliance with applicable regulations and provides recommendations for aligning the credit scoring system with regulatory requirements in the digital multifinance sector.

3.2 Digital Multifinance Financing Application Flow Process

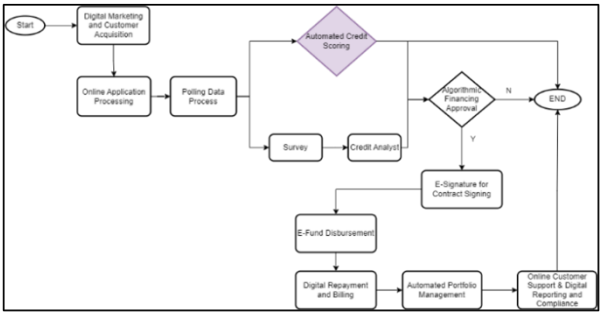

Fig. 1. Multifinance Digital Business Process

The business process for multifinance companies in Indonesia involves a comprehensive digital workflow form customer acquisition to financing settlement. Initially, digital marketing strategies are employed to attract potential customers, who can then access and complete financing applications online. Data is collected and processed to support credit assessment, followed by automated credit scoring using algorithms to evaluate customer creditworthiness efficiently. Additional surveys and credit analyst evaluations may be conducted to gather more information. Financing approvals are algorithmically decided, and electronic signatures are used for contract signing. Funds are disbursed electronically, and digital technology manages repayment and billing processes. Automated portfolio management tracks financing status, regulatory compliance and customer service. This digital approach enhances efficiency, transparency, and accessibility in the multifinance industry.

3.3 Systematic Development of a Credit Scoring Model

This study developed a Credit Scoring model using Python based machine learning integrated with Django frameworks. It aims to predict credit risk accurately for applicants, ensuring efficient assessment of customer eligibility in financing applications. Keys steps include data pre-processing, algorithm selection, model training, evaluation, parameter tuning, and model deployment via serialization of Python objects. The system utilizes an API for swift processing, enhancing real-time application in multifinance operations.

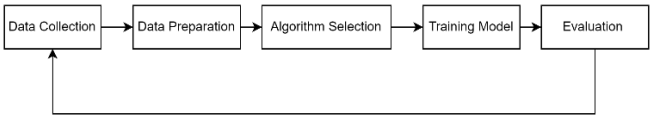

Fig. 2. Credit Scoring Model System

3.4 Economic Analysis

The economic analysis in this study involves both business feasibility analysis, utilizing data from the web-based credit scoring system. The structured framework follows the cost structure encompasses development, maintenance, marketing, compliance, and security expenses.

This analysis evaluates the credit scoring system's economic sustainability for digital multifinance companies, focusing on revenue, costs (CAPEX and OPEX), and key financial metrics like IRR, NPV, PP, PI. The results provide a comprehensive overview of the system's long-term profit potential and economic impact within the digital multifinance sector.

3.5 Regulation Analysis

The regulatory analysis in this study examines the impact of government regulations and policies on the growth of the digital multifinance industry, with a focus on credit scoring systems. It includes the assessment of licensing requirements, operational supervision, and data security provisions. The analysis also addresses the integration of machine learning and algorithms in credit scoring, alongside privacy and data security regulations to protect consumers. Furthermore, the involvement of third-party collaborations with credit institutions and technology companies is considered. Essential information for this research includes details on the digital technologies used in the multifinance industry, user data, relevant national and international regulations, and formulated scenarios for the study.

4 Results and Discussion

4.1 Results of Credit Scoring Model System

This section presents the results of credit scoring model system.

The feature selection analysis of the credit scoring model has yielded significant insights into the variables that most strongly influence creditworthiness. Through a comprehensive evaluation of 14 features, we identified those that contribute maximally to the model's performance, enhancing prediction accuracy and interpretability.

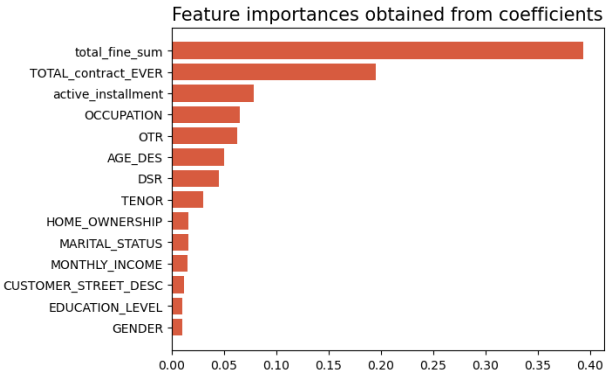

Fig. 3. Feature Importances Graphic

The Analysis reveals several key findings in the assessment of credit risk. Among important features, "Total Fine" stands out as the primary indicator, suggesting that the total amount of fines incurred is crucial in evaluating credit risk. Additionally, the "Total Contracts Ever" feature, reflecting the customer's history of borrowing, and "Active Installment," which indicates ongoing financial obligations, play significant roles in credit decisions. Features of medium importance include "Occupation," which reflects income stability and job security, "OTR (Price/Requested Amount)," offering insights into the borrower's financial commitments, "Age," which helps assess risk based on life stage, and "DSR (Debt Service Ratio)," measuring the borrower's ability to manage debt relative to their income. Finally, "Tenor (Loan Term)" is noted as having lover importance in the analysis, being less influential compared to other factors in determining creditworthiness.

4.2 Results of Model Selection

The developed credit scoring model using XGBoost algorithm shows a good level of accuracy with 70% accuracy on training data and 69% on test data, with a precision rate of 75% and a ROC value of 87%.

4.3 Results of Evaluation Performance

The model performance evaluation of the credit scoring system provides a detailed assessment based on critical metrics, including accuracy, precision, recall, and F1-Score, for both the training and testing datasets. This evaluation offers a comprehensive understanding of the model's capability to accurately and consistently predict creditworthiness, ensuring its reliability in credit decision making.

Classification report Data Train :

	precision	recall	f1-score	support
0	0.76	0.68	0.71	234214
1	0.54	0.65	0.59	164652
2	0.79	0.76	0.77	207884
accuracy			0.70	606750
macro avg	0.70	0.70	0.69	606750
weighted avg	0.71	0.70	0.70	606750

Fig. 4. Feature Importances Graphic

The F-1 score reflects a good balance between precision and recall, indicating solid performance. These metrics suggest that the model performs well on the training data, with high precision and recall demonstrating its ability to minimize false positives and false negatives. This indicates a strong ability to classify customers correctly as creditworthy or non-creditworthy.

Classification report Data Test :

	precision	recall	f1-score	support
0	0.75	0.67	0.70	100231
1	0.53	0.63	0.57	70864
2	0.78	0.75	0.76	88942
accuracy			0.69	260037
macro avg	0.68	0.68	0.68	260037
weighted avg	0.70	0.69	0.69	260037

Fig. 5. Classification Report Data Test

The F-1 score strikes a balance between precision and recall, with the model demonstrating slightly lower yet consistent performance on test data, indicating strong generalizability. The high precision reflects the model's ability to minimize incorrect predictions of creditworthiness, while good recall showcases its effectiveness in accurately identifying genuinely creditworthy cases.

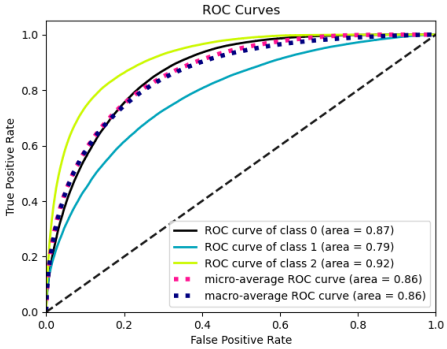

Fig. 6. ROC Curve

With a ROC AUC value of 87%, the model exhibits a strong capability to differentiate between creditworthy and non- creditworthy applicants, underscoring its accuracy and reliability in credit scoring. This metric is particularly important as it integrates both the true positive rate and false positive rate, offering a comprehensive assessment of the model's overall performance.

The developed credit scoring system model was subsequently implemented into a web-based application using the Python framework, Django. This application, named mdcscore.com, is designed to deliver credit decisions to customers who have filled out or submitted applications through the system. The credit decisions generated by the classification model fall into three categories approved, under consideration, or rejected. These decisions are then communicated to the customers via WhatsApp notifications. This analysis includes a detailed explanation of the credit scoring system model development, the process of converting it into a web application using Django, and the mechanism for notifying customers of credit decisions. Additionally, it covers technical aspects such as API integration, data security, and system resource management.

4.4 Results of Economic Analysis

To fulfill the business model aspects of the credit scoring system in this multifinance company, it is essential to complement analysis by assessing management and financial aspects. This analysis is necessary to determine whether the system is worthy of investment.

Table 1. OPEX

Type	Segment	Total
OPEX	Employee salary	$ 1.160.012,58
	Development System	$ 131.165,53
	Office Supplies	$ 164.280,35

Type	Segment	Total
	Ads	$ 1.954,36
	Depreciation	$ 9.522,58
	Cumulative Depreciation	$ 793.434,93

The total OPEX for this 6-year period shows that significant costs mainly come from employee salaries and accumulated depreciation. These expenditures reflect substantial investment in human resources and system development, which are crucial for supporting the long-term success of the credit scoring project. By understanding this cost composition, the project can better allocate resources and plan finances to ensure the project remains sustainable and delivers long-term value.

Table 2. Total Capex

Type	Segment	Total Price in USD
CAPEX	Asset	$ 19.384,62
	Expert	$ 20.192,31
	R&D	$ 11.025,64
	Regulation Fees	$ 3.205,13
	Unexpected Cost	$ 3.615,38
	Total CAPEX Others	$ 3.615,38

The total CAPEX for the 6 periods on the credit scoring system project shows that the largest expenditures are for experts and asset acquisition. These expenditures reflect a significant investment in the expertise and infrastructure necessary to build a reliable and regulatory-compliant credit scoring system. By understanding this cost distribution, the company can more effectively plan its budget and manage the risks associated with the development and implementation of the credit scoring system project.

Table 3. Feasibility Results

WACC	9,5 %
NPV	$ 62.772,25
IRR	22 %
MIRR	17%
PP	4,4
PI	1,09663

The feasibility analysis of the credit scoring system project reveals its financial viability, with key indicators supporting this conclusion. The Net Present Value (NPV)

stands at $ 62.772,25 indicating profits greater than the invested capital after discounting future cash flow at a 9,5 % Weighted Average Cost of Capital (WACC). The Internal Rate of Return (IRR) is 22 % surpassing the WACC, demonstrating profitability. The Payback Period (PP) is 4 years and 4 months, indicating a swift recovery of the initial investment dan reducing risk. Additionally, the Profitability Index (PI) of 1,09663, while modest is positive when considered alongside the NPV and IRR, aligning well with strategic business goals. Overall, the project effectively balances risk with returns, confirming its status as a profitable investment.

The OPEX and CAPEX data highlight key financial investments in the credit scoring system project, with significant costs in employee salaries and accumulated depreciation under OPEX, and asset acquisition and expert fees under CAPEX. These expenditures reflect a strategic focus on human resources, infrastructure, and specialized expertise. The financial viability is confirmed by the feasibility analysis, which shows a positive NPV, strong IRR, and a reasonable payback period, indicating that the project is both profitable and aligns with long-term business goals. Together, these financial metrics support the project's overall sustainability and strategic value.

4.5 Results of Regulations Analysis

The analysis of the digital multifinance sector underscores several pivotal factors affecting the adoption and success of digital credit scoring technologies. Digital multifinance companies must continually adapt to the latest technological innovations in credit assessment. Rapid technological changes require the ability to continuously learn and adapt to remain competitive. Failure to adapt can lead to companies falling behind and losing competitiveness in the market. Companies that fail to keep up with technological advancements may not be able to offer efficient and competitive services, thus losing market share. Furthermore, the development of digital credit scoring technology requires substantial investment in research and development, technology infrastructure, and skilled human resources. This includes purchasing hardware and software, employee training, as well as developing and maintaining advanced and secure systems. Therefore, small and medium sized digital multifinance companies face significant barriers to compete in a highly competitive global environment. These high costs are often unsustainable for small companies, causing them to lag larger firms with greater resources. As a result, small and medium-sized companies may struggle to leverage the latest technology to enhance the efficiency and accuracy of their credit assessments.

Complex policies and regulations in the financial industry often limit companies' ability to implement new technologies quickly. Stringent regulations aim to protect consumers and maintain financial stability but can hinder innovation. The digital credit scoring industry in Indonesia faces significant challenges due to uncertainty in regulations and governing rules. The rapid pace of technological advancement and market dynamics often outpaces regulators' ability to adjust existing regulations or create new guidelines. Lack of clarity in regulations like these can lead to confusion and uncertainty among companies operating in this sector. For instance, when regulations do not explicitly address or provide guidance on the use of new technologies in credit assessment processes, companies may hesitate to adopt such innovations due to uncertainty

about compliance with applicable regulations.

Despite regulations such as POJK No.13/POJK.03/2020 and POJK No.22 of 2023, challenges in their implementation and enforcement persist. Existing regulations need to be consistently and effectively enforced to support the development of digital multifinance companies navigating the complex regulatory framework, which can hinder innovation and growth. Moreover, suboptimal support from the government and regulators in facilitating the adoption and development of digital credit scoring systems exacerbates these challenges. Governments and regulators play a crucial role in creating an environment that supports technological innovation in the financial sector. The impact on growth and innovation in the digital multifinance sector remains limited, potentially hindering increased access to financial services and contributing to economic growth. Without adequate support, digital multifinance companies will struggle to develop and implement technology effectively.

Personal data protection is a crucial problem in the collection. Storage, and use of data by digital multifinance companies. The risks of data breaches and privacy violations are increasing with the widespread adoption of digital technology. These risks can undermine consumers' trust in digital financial services. Consumer trust is crucial for the successful adoption of new technologies; without it, digital multifinance companies will struggle to attract and retain customers.

The analysis also highlights the opportunities provided by government and regulatory support, such as the OJK initiatives and the Regulatory Sandbox, which encourage the development of digital financial ecosystems. Enhanced financial inclusion and partnership with technology risk, and resistance from industry players reliant on traditional system pose significant threats to the sector. Companies must navigate these challenges by investing in cybersecurity and risk management to maintain consumer trust and secure their market position.

4.6 Comparative Study of Regulations in Other Countries

Credit scoring system hold significant potential for enhancing financial inclusion in Indonesia, particularly for underserved segments. However, developing these systems requires careful consideration of risks, such as data privacy, cybersecurity, and potential discrimination. Indonesia's regulatory framework, guided by OJK, regulations NO.5/POJK/.03/2022 and the more flexible approach of regulation Np. 13/POJK/02/2018, supports innovation while ensuring compliance and consumer protection. Learning from countries like the United States, China. the United Kingdom, and Sout Korea, Indonesia can leverage advanced digital infrastructure and regulatory support to develop inclusive and accurate credit scoring models. These countries' experiences demonstrate the importance of regulatory frameworks, fintech innovation, and strong collaboration among stakeholders in creating effective credit scoring ecosystems.

In other countries, such as the United States, China, the United Kingdom, and South Korea, regulations play a crucial role in the development and impersonation of credit scoring systems. In the United States, the Equal Credit Opportunity Act (ECOA) requires credit scoring systems to test their models before being used for lending and

mandates lenders to provide reasons for credit application rejections within 30 days. The Fair Credit Reporting Act (FCRA) introduces legal definitions for entities involved in consumer reporting and protects consumer data privacy. In China, credit scoring system encompasses both financial and social creditworthiness assessments, although they face challenges related to data privacy and assessment accuracy. South Korea has established AI guidelines for financial services through the financial services commission and focuses on promoting the use of AI in the financial sector. The United Kingdom, through the Financial Conduct Authority, oversees AI practices in financial services industry. These countries illustrate the importance of supportive regulations and collaboration between the fintech sector and regulators in creating effective and fair credit scoring ecosystems.

To strengthen the regulatory framework for credit scoring systems in Indonesia, several specific steps can be taken based on the experiences of other countries. Indonesia could require credit scoring models to undergo testing, similar to practices in the United States, to ensure fairness and transparency, including providing reasons for credit rejections within 30 days. Strengthening consumer data privacy protections, as outlined in the U.S. FCRA, is also crucial to prevent data misuse. OJK may adopt guidelines for the use of AI in financial services, following the example of South Korea, to minimize bias and enhance transparency. Collaboration between fintech companies and traditional financial institutions, as seen in the United Kingdom, could promote innovation and foster the development of more inclusive credit scoring models. Additionally, the use of non-financial data, as practiced in China, could help underserved populations gain access to credit, provided that privacy risks are effectively managed. These steps would support the development of a fair and inclusive credit scoring ecosystem in Indonesia.

5 Recommendations For Regulations

5.1 Specific and Comprehensive Regulations

The financial Services Authority (OJK) should establish detailed and comprehensive regulations governing credit scoring providers for multifinance companies in Indonesia. These regulations must include clear definitions, general provisions, and structured licensing procedures. The aim is to ensure transparency and operational efficiency, allowing companies to understand and fulfill the requirements necessary for obtaining operational permits.

5.2 Advance Procedures and Regulatory Clarity

It is crucial to develop advanced procedures that provide clarity on the steps multifinance companies must follow in achieving registered status and receiving sandbox recommendations. These procedures should outline the administrative, technical, and financial criteria required for obtaining full operational permits. By offering clear

guidelines, OJK can facilitate a smoother and quicker licensing process, enabling companies to commence official operations without unnecessary delays.

5.3 Consumer Data Protection

OJK must not only implement detailed regulations but also ensure continuous oversight regarding the protection of consumer data within credit scoring systems. This includes setting strict protocols for data collection, storage, and usage, with severe penalties for any breaches of privacy or mishandling of personal information. Furthermore, it is crucial to establish a data security certification system to audit and verify the compliance of multifinance companies with these standards. Public trust in digital financial services is contingent on the assurance of data safety, and the regulations must evolve in tandem with technological threats to stay relevant.

5.4 Legal Certainty and Protection

To enhance legal certainty and investor confidence, OJK should define explicit rules for the licensing process that follows the regulatory sandbox and registered status. These rules should include specific timelines for submission and approval, as well as mechanisms for compliance assessment and ongoing monitoring. Establishing clear legal frameworks will reinforce trust in the multifinance industry.

5.5 Increased Collaboration and Participation

Collaboration between OJK and industry stakeholders must be a central component of regulatory development. OJK should establish formal working groups that involve not just academics and fintech practitioners, but also data privacy experts and consumer protection bodies. This collaboration would ensure that multifinance regulations align with global standards and address both innovative opportunities and potential risks. Additionally, encouraging more frequent public consultations and joint research efforts will ensure that the regulations remain agile, reflective of market needs**,** and can adapt quickly to advancements in fintech and digital credit scoring systems.

Conclusion

The analysis of the mdcscore.com credit scoring system from technical, economic, and regulatory perspectives demonstrates its feasibility and potential for successful implementation in Indonesia. Technically, the credit scoring model, utilizing XGBoost, exhibits a commendable accuracy rate, highlighting the effectiveness of feature selection such as fines received, number of contracts, and active installments as critical indicators of credit risk. Economically, the project shows promising financial metrics with a positive NPV, favorable IRR and MIRR, and a short payback period, indicating a robust investment opportunity with manageable risk and significant long-term benefits.

Regulatory analysis emphasizes the need for comprehensive and clear regulations from the Financial Services Authority (OJK) to support the implementation and operation of the credit scoring system. Specific regulations should cover licensing procedures, operational permits, and consumer data protection to ensure transparency and legal certainty. Moreover, advanced procedures and robust collaboration with stakeholders are essential to accommodate technological advancements and market dynamics. Overall, with effective regulatory support, careful financial planning, and robust technical implementation, the mdcscore.com credit system is well-positioned for success in enhancing credit assessment processes in the digital multifinance sector.

References

1. A. V. Thakor, "Fintech and banking: What do we know?," *J. Financ. Intermediation*, vol. 41, no. July, 2020, doi: 10.1016/j.jfi.2019.100833.
2. F. E. A. J. Awotunde, E. A. Adeniyi, R. Ogundokun, Fintech with Artificial Intelligence, Big Data, and Blockchain. 2021.
3. D. R. Pyriana, H. Akbar, M. M. Rifa'i, S. K. Wardani, S. Inayah, and M. R. Shihab, "IT Capabilities Analysis Towards the Organization Performance in the Virtual Organization: A Case Study of ABC Multifinance Company in Indonesia," in *2022 International Conference on Informatics, Multimedia, Cyber and Information System (ICIMCIS)*, Nov. 2022, pp. 1–6. doi: 10.1109/ICIMCIS56303.2022.10017921.
4. G. Change *et al.*, "Exploring the Strategies Big Data Analysts Need to Implement When Establishing Community Bank Data Governance," *Pap. Knowl. . Towar. a Media Hist. Doc.*, vol. 3, no. 2, p. 6, 2021.
5. A. Y. Syariful, Saparso, and R. Lumbantobing, "The effect of product innovation and service quality on customer loyalty is mediated by customer satisfaction at PT KB Finansia Multifinance (Kredit plus) Tasikmalaya," *Enrichment : Journal of Management*, vol. 13, no. 1. pp. 596–611, 2023. doi: 10.35335/enrichment.v13i1.1303.
6. A. A. Diniyya, M. Aulia, and R. Wahyudi, "Financial Technology Regulation in Malaysia and Indonesia: A Comparative Study," *Ihtifaz J. Islam. Econ. Financ. Bank.*, vol. 3, no. 2, p. 67, 2021, doi: 10.12928/ijiefb.v3i2.2703.
7. X. Dastile, T. Celik, and M. Potsane, "Statistical and machine learning models in credit scoring: A systematic literature survey," *Appl. Soft Comput. J.*, vol. 91, p. 106263, 2020, doi: 10.1016/j.asoc.2020.106263.
8. Z. A. Andriawan, R. Pratama, and Khadijah, "Usability Testing of Multifinance Mobile Application for End-Customer (Case Study: PT.XYZ)," *ICICoS 2020 - Proceeding 4th Int. Conf. Informatics Comput. Sci.*, 2020, doi: 10.1109/ICICoS51170.2020.9298977.
9. H. Karjaluoto, A. A. Shaikh, H. Saarijärvi, and S. Saraniemi, "How perceived value drives the use of mobile financial services apps," *Int. J. Inf. Manage.*, vol. 47, no. September 2017, pp. 252–261, 2019, doi: 10.1016/j.ijinfomgt.2018.08.014.
10. J. P. Barddal, L. Loezer, F. Enembreck, and R. Lanzuolo, "Lessons learned from data stream classification applied to credit scoring," *Expert Syst. Appl.*, vol. 162, no. July, p. 113899, 2020, doi: 10.1016/j.eswa.2020.113899.
11. F. Ariq, F. Adiwirya, Y. H. Chrisnanto, A. K. Ningsih, and F. Renaldi, "Car Creditworthiness Classification Using Naive Bayes and Credit Scoring," no. Luhriyani 2016, pp. 992–1001, 2023, doi: 10.46254/ap03.20220199.

12. A. Akbar, M. A. B. A. Majid, and A. A. Mokhtar, “Life cycle costing of thermal energy storage system using CAPEX and OPEX,” *J. Mech. Sci. Technol.*, vol. 35, no. 7, pp. 3223–3229, 2021, doi: 10.1007/s12206-021-0642-9.
13. Ardyn Sari Sinaga *et al.*, “Comparison of capital budgeting methods: NPV, IRR, PAYBACK PERIOD,” *World J. Adv. Res. Rev.*, vol. 19, no. 2, pp. 1078–1081, 2023, doi: 10.30574/wjarr.2023.19.2.1483.
14. FINANCIAL SERVICES AUTHORITY OF THE REPUBLIC OF INDONESIA, “Digital Finance Innovation Road Map and Action Plan 2020-2024,” p. 9, 2020.
15. Indonesia, “Regulation of the Financial Services Authority of the Republic of Indonesia Number 7/POJK.05/2022,” *Financ. Serv. Auth. Repub. Indones.*, pp. 1–8, 2022.
16. OJK, “POJK No 29/POJK.05/2014,” 2014.
17. Bank Indonesia, “Bank Indonesia Regulation Number 23/2/PBI/2021,” *Www.Ojk.Go.Id*, vol. 53, no. 9, pp. 1689–1699, 2021, [Online]. Available: https://www.ojk.go.id/
18. FINANCIAL SERVICES AUTHORITY OF THE REPUBLIC OF INDONESIA, “Electronic Information And Transactions Law In Number 1 of 2024,” no. 1, pp. 1–3, 2004, [Online]. Available: https://www.ojk.go.id/
19. D. B.-B. RI and Bpk.go.id, “Personal data protection law,” *Ditama Binbangkum - BPK RI*, no. 016999, pp. 1–50, 2022.