



Department of Digital Business

Journal of Artificial Intelligence and Digital Business (RIGGS)

Homepage: <https://journal.ilmudata.co.id/index.php/RIGGS>

Vol. 5 No. 1 (2026) pp: 12601-12609

P-ISSN: 2963-9298, e-ISSN: 2963-914X

Adoption of Explainable Artificial Intelligence in Decision Support Systems under Complex Data Environments

Hikmah Adwin Adam^{1*}, Pierre Marcello Lopulalan², Meryatul Husna³

^{1,2}Politeknik Negeri Medan, Indonesia

³Politeknik Pelayaran Banten, Indonesia

*hikmahadam@polmed.ac.id

Abstract

The increasing complexity of data in the digital banking industry in Indonesia has encouraged the use of Decision Support Systems (DSS) based on Artificial Intelligence (AI), especially in the credit scoring process. However, the black-box characteristics of conventional AI models pose problems related to transparency, trust, and regulatory compliance, especially in credit decision-making that has a direct impact on customers. This study aims to analyze the adoption of Explainable Artificial Intelligence (XAI) in DSS in credit scoring systems in Indonesian digital banking, with an emphasis on how XAI can improve model interpretability in complex and heterogeneous data environments. The research approach used is mixed-methods, which combines quantitative analysis of the performance of the XAI model with a qualitative study through case studies on digital banking institutions. The results show that the implementation of XAI is able to improve the clarity of credit decisions without sacrificing predictive accuracy significantly, especially through the use of post-hoc explainability techniques and hybrid models. In addition, organizational readiness, compliance with Financial Services Authority (OJK) regulations, and data governance maturity are the main determinants in the success of XAI adoption. This research contributes theoretically through the development of a conceptual framework that integrates the dimensions of model clarity, data complexity, and decision quality in the context of digital banking. In practical terms, these findings provide strategic implications for the development of a transparent, accountable, and trust-oriented DSS, thereby supporting fairer and more accountable credit decision-making in Indonesia.

Keywords: XAI, DSS, Credit Scoring, Digital Banking, Interpretability, Quality Of Decisions.

1. Background

Digital transformation in the banking industry in Indonesia has driven a significant increase in the use of large-scale and diverse data to support decision-making processes. Digital banking now relies on various data sources, ranging from transaction data, user behavior, to alternative data, which are complex, unstructured, and dynamic [1]. In this context, Artificial Intelligence (AI)-based Decision Support Systems (DSS) are a key component, especially in the credit scoring process which demands high accuracy and speed in evaluating customer creditworthiness [2].

Although AI models such as machine learning and deep learning offer superior predictive performance, their black-box characteristics pose serious challenges in terms of transparency and accountability. The inability to explain the basis for the model's decision-making has the potential to reduce the level of stakeholder trust, both on the customer and regulatory sides [3], [4]. In the context of Indonesian digital banking, this is increasingly crucial given the demands for compliance with Financial Services Authority (OJK) regulations that emphasize the principles of prudence (prudential banking) and consumer protection. Thus, the need for a system that is not only accurate but also explainable is becoming increasingly urgent [5].

In response to these problems, the concept of Explainable Artificial Intelligence (XAI) emerged as an approach that aims to improve the interpretability and transparency of AI models without significantly sacrificing their predictive performance [6]. XAI enables stakeholders to understand the logic behind the decisions generated by the system, thereby increasing trust, supporting auditability, and facilitating regulatory compliance. In the context of credit scoring, the implementation of XAI is important to ensure that credit decisions are fair, non-discriminatory, and accountable.

However, the adoption of XAI in DSS in Indonesia's digital banking environment still faces various challenges [7]. High data complexity, limited technology infrastructure, organizational readiness, and the level of maturity of data governance are factors that affect the success of implementation [8]. In addition, there is a gap between XAI's technical development in the academic realm and its application in the industrial sector, especially in the local context of Indonesia, which has its own regulatory characteristics and digital ecosystem. Therefore, a comprehensive study is needed to understand how XAI can be effectively adopted in DSS, as well as what factors are determinants of its success.

Based on this background, this study aims to analyze the adoption of XAI in DSS in credit scoring systems in Indonesian digital banking, with a focus on improving model interpretability in complex and heterogeneous data environments. This study uses a mixed-methods approach that combines quantitative analysis of the performance of the XAI model with a qualitative study through a case study on digital banking institutions. This approach is expected to be able to provide a holistic understanding, both from the technical and contextual aspects of the organization.

The contribution of this research is two-way. Theoretically, this study develops a conceptual framework that integrates the dimensions of model clarity, data complexity, and decision quality in the context of AI-based DSS. This framework is expected to enrich the literature on XAI adoption, especially in the digital finance sector. Practically, this research provides strategic implications for banking industry players in designing a transparent, accountable, and user trust-oriented DSS. Thus, the results of this research are expected to support fairer, more inclusive, and good governance decision-making in Indonesia

2. Research Methods

This study uses a mixed-methods approach with a sequential explanatory design that integrates quantitative and qualitative analysis sequentially [9]. This approach was chosen to provide a comprehensive understanding of the adoption of Explainable Artificial Intelligence (XAI) in Decision Support Systems (DSS) in credit scoring systems in Indonesian digital banking. The initial stage of the research was focused on quantitative evaluation of model performance, followed by an in-depth qualitative exploration to understand the contextual factors that influence the implementation of XAI.

2.1. Research Design

The research design used is sequential explanatory, where quantitative analysis is carried out first to test the performance and level of model interpretability, then followed by qualitative analysis to deepen understanding of the quantitative results. This approach allows for the integration of the model's technical measurement results with the practical perspective of the digital banking organization, resulting in a more holistic analysis [10].

2.2. Data and Data Sources

The data in this study consists of quantitative and qualitative data. Quantitative data is in the form of a credit scoring dataset that includes customer demographic variables, credit history, transaction behavior, and alternative data that are relevant in the context of digital banking. This dataset is obtained from secondary sources that have been anonymized to maintain the confidentiality of information [11]. Meanwhile, qualitative data was obtained from interviews with stakeholders in digital banking institutions, such as risk analysts, AI system developers, as well as management and compliance, and supported by applicable internal policy and regulatory documents.

2.3. Data Collection Techniques

Quantitative data collection is carried out through the processing of historical credit scoring datasets that are relevant to the research context [12]. The qualitative data was collected through semi-structured interviews aimed at exploring the experiences and perceptions of informants related to the implementation of XAI in DSS [13]. In addition, a documentation study was conducted on internal organizational policies and regulations from the Financial Services Authority (OJK), as well as limited observations on system implementation practices in the operational environment.

2.4. Quantitative Data Analysis Techniques

Quantitative analysis was carried out by comparing the performance of several models, namely black-box models such as Random Forest and Gradient Boosting, interpretable models such as Logistic Regression and Decision Tree, and hybrid models that utilize XAI techniques such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations). The evaluation was carried out using performance metrics such as accuracy, precision, recall, and AUC (Area Under Curve), as well as interpretability indicators measured based on the clarity and consistency of the model's explanation of the prediction output.

2.5. Qualitative Data Analysis Techniques

Qualitative data analysis was carried out using a thematic analysis approach. This process begins with the transcription of the interview results, followed by open coding to identify the unit of meaning, then grouping into categories and main themes. The final stage is in the form of interpreting the relationship between themes to identify factors that affect the adoption of XAI, such as organizational readiness, compliance with OJK regulations, and the level of maturity of data governance in digital banking institutions.

2.6. Validity and Reliability

To ensure the validity and reliability of the research, triangulation techniques between quantitative and qualitative data are used to strengthen the consistency of findings. In addition, member checking was carried out on informants to verify the results of the interviews, as well as the application of cross-validation in quantitative model testing to ensure the stability and reliability of the analysis results.

2.7. Research Conceptual Framework

This research develops a conceptual framework that integrates three main dimensions, namely data complexity, model clarity through XAI, and decision quality. This framework was used to analyze how the implementation of XAI in DSS can improve transparency and accountability in credit decision-making in Indonesia's digital banking. Thus, the methodological approach used is expected to be able to make a comprehensive contribution both theoretically and practically.

3. Results and Discussion

This section presents the results of research obtained through a mixed-methods approach, which consists of two main stages, namely quantitative analysis and qualitative analysis. The presentation of results is carried out in an integrated manner by placing empirical evidence in the form of tables and interview excerpts to strengthen the interpretation of the findings.

3.1. Model Performance and Interpretability

Quantitative analysis was carried out to evaluate the performance of the credit scoring model as well as the level of interpretability generated through the XAI approach. The test used a dataset of 10,000 observations using the train-test split (80:20) and 5-fold cross-validation method. The results showed that the black-box model had the highest predictive performance, with the AUC Gradient Boosting value of 0.881 ± 0.011 and the Random Forest of 0.872 ± 0.013 . However, this model has limitations in terms of interpretability. In contrast, interpretable models such as Logistic Regression and Decision Tree have a higher level of clarity, but with relatively lower performance.

Table 1. Comparison of Model Performance and Interpretability

Models	Accuracy (\pm SD)	AUC (\pm SD)	Interpretability
Logistic Regression	0.782 ± 0.018	0.801 ± 0.015	Height
Decision Tree	0.803 ± 0.016	0.821 ± 0.014	Height
Random Forest	0.851 ± 0.013	0.872 ± 0.013	Low

Gradient Boosting	0.863 ± 0.012	0.881 ± 0.011	Low
RF + SHAP (XAI)	0.842 ± 0.015	0.861 ± 0.014	Height
GB + LIME (XAI)	0.834 ± 0.017	0.853 ± 0.016	Medium-High

Based on Table 1, XAI-based models are able to maintain performance with a relatively small AUC difference (<2%) compared to black-box models, while improving interpretability. This shows that XAI's approach is effective in balancing accuracy and transparency in DSS.

3.2. The Effect of Data Complexity on XAI

In addition to model performance, this study also examines the effect of data complexity on the effectiveness of the XAI method. Data complexity is measured based on the number of features, the heterogeneity of the data source, and the level of class imbalance ratio. The test was conducted by comparing the interpretation stability and model performance at three levels of data complexity. The results show that the XAI method has different levels of stability depending on the complexity of the data. In general, increased data complexity tends to decrease the stability of interpretation, especially in locally-based methods such as LIME.

Table 2. Stability of XAI Methods at Different Levels of Data Complexity

Data Complexity	XAI Method	Interpretation Stability	Accuracy (±SD)
Low	LIME	Height	0.821 ± 0.014
Medium	LIME	Medium	0.833 ± 0.016
Height	LIME	Low	0.812 ± 0.018
Low	SHAP	Height	0.834 ± 0.013
Medium	SHAP	Height	0.842 ± 0.012
Height	SHAP	Height	0.839 ± 0.015

Table 2 shows that the SHAP method has more consistent interpretation stability than LIME, especially in high-complexity datasets. These findings indicate that in complex and heterogeneous data environments, the choice of XAI methods should consider aspects of interpretation stability in addition to model accuracy.

3.3. Organizational and Regulatory Factors

Qualitative analysis was conducted to identify contextual factors influencing the adoption of XAI in digital banking. Based on the results of interviews and case studies, it was found that there are three main factors that play a significant role, namely organizational readiness, regulatory compliance, and data governance maturity. To provide a systematic overview, the findings are summarized in the following table:

Table 3. Determining Factors for XAI Adoption in Digital Banking

Factors	Influence Level	Description
Organizational Readiness	Height	Infrastructure and HR
Regulation (OJK)	Very High	Transparency and auditing
Data Governance	Height	Data quality and integration

This result is reinforced by the following informant statements:

"Regulators' demands for transparency in the credit decision-making process are increasing. Without an explanation mechanism like XAI, we face difficulties in providing acceptable justification, especially in the audit and oversight process." (Informant I-03, Compliance Manager, interview dated March 12, 2025)

"The implementation of XAI is not only dependent on technology, but also highly determined by the readiness of the organization, especially in terms of the quality of the available data as well as the competence of human resources in managing and interpreting AI models." (I-07 Informant, Head of Data, interview on March 18, 2025)

The citation shows that non-technical factors, such as organizational readiness and regulatory pressures, have a significant role and are inseparable from the technical aspects in driving the successful adoption of XAI on Decision Support Systems in digital banking.

3.4. Implications for Credit Decision Quality

In addition to adoption factors, this study also examines the impact of XAI implementation on the quality of credit decisions. The results of the analysis showed an increase in the aspects of transparency, accountability, and user trust.

Table 4. The Impact of XAI Implementation on Credit Decisions

Aspects	Before XAI	After XAI
Transparency	Low	Height
Trust	Medium	Height
Risk of Bias	Height	Lower
Audit Facility	Low	Height

The empirical findings were also reinforced through interviews with practitioners directly involved in the development and use of AI-based DSS, in order to understand the implications of the application of XAI in real practice.

"With the implementation of XAI, we are not only focusing on the credit score, but also being able to understand the factors underlying those decisions, making the analysis process more transparent and accountable." (I-05 Informant, Credit Analyst, interview dated March 20, 2025)

"XAI provides the ability to identify potential biases in models that were previously difficult to detect, allowing for more systematic and sustainable model improvement." (Informant I-09, AI Engineer, interview on March 22, 2025)

This shows that the implementation of XAI not only improves the technical quality of DSS in terms of accuracy and interpretability, but also contributes significantly to strengthening the aspects of ethics, transparency, and governance in the credit decision-making process.

Discussion

The main findings of this study show that the adoption of Explainable Artificial Intelligence (XAI) in Decision Support Systems (DSS) for credit scoring in Indonesian digital banking is able to increase decision interpretability without significantly degrading predictive performance. These results are in line with recent literature trends that position XAI in response to the need for transparency, accountability, and trust in AI-based DSS, particularly in high-risk domains such as finance [14]. A systematic review in finance also shows that tasks such as credit management, stock price prediction, and fraud detection are the dominant areas of XAI implementation, with SHAP, feature importance, and rule-based methods being the most widely used approaches [2]. In the context of DSS, explainability is seen as not just an additional feature, but a prerequisite for the system to be accepted by users, audited, and used responsibly [15].

Theoretically, these results reinforce the view that the quality of DSS is determined not only by accuracy, but also by the ability of the system to generate meaningful explanations for decision-makers. In the perspective of information systems science and DSS, explanations serve as a mechanism to reduce uncertainty, increase confidence calibration, and support accountable decision-making. Coussement et al. emphasized that XAI needs to be understood as part of efforts to strengthen decision-making, not just to "open the black box", but to ensure that the model's output can be translated into a basis for actions that are relevant to humans [16]. It is also consistent with Miller's argument that a good explanation should be close to the way humans understand cause, choose the most relevant reasons, and judge decisions in a given social context. Thus, the findings of this study confirm that XAI's success in digital banking is not only measured by the performance of the model, but also by the quality of explanations that can be understood by risk analysts, auditors, and even customers.

Quantitative findings that show that hybrid models, namely black-box models equipped with post-hoc explainability techniques such as SHAP or LIME, achieve a relatively good balance between accuracy and interpretability are also relevant to previous research [17]. Nwafor et al. show that a hybrid approach to credit decisions can improve transparency and fairness without having to sacrifice model effectiveness. These findings explain why in this study the hybrid model is more realistic for Indonesia's digital banking environment which faces pressure to remain competitive in prediction accuracy, but at the same time must meet the demands of accountability. In practice, organizations tend not to completely abandon complex models because they often excel at capturing nonlinear patterns and variable interactions in large, heterogeneous digital transaction data. Therefore, XAI in the form of post-hoc explanation becomes an operational middle ground: it does not replace the performance of the model, but adds a layer of justification that can be used in decision evaluation [18].

However, the results of this study also need to be read critically because not all literature supports the dominance of the hybrid model. Rudin emphatically argues that in high-risk decisions, an inherently interpretable model should take precedence over simply "explaining" the black-box model [19]. Associated with the findings of this study, there are important conceptual tensions: on the one hand, the empirical results show that post-hoc XAI is still useful and pragmatic; On the other hand, normatively there is a strong argument that a truly understandable model from the outset is safer for decisions that directly impact the individual. This difference can be explained by the context of the application. In a highly dynamic digital banking environment, alternative data, transaction behavior, and risk patterns tend to be more complex than can be optimally captured by a simple linear model [20]. Therefore, the findings of this study do not reject Rudin's criticism, but show that in industry practice, XAI adoption often moves within a spectrum of compromises between performance, clarity, and business needs.

The results of this study also show that data complexity is a factor that greatly determines the effectiveness of XAI. The finding that SHAP tends to be more stable than LIME on more complex and unbalanced data is in line with Chen et al.'s study of imbalanced credit scoring datasets, which showed that the interpretive stability of SHAP and LIME decreased as class imbalances increased, although the impact was more pronounced on LIME [21]. The scientific implication is that interpretability is not a stand-alone trait, but rather is influenced by the quality and structure of the data. This means that the explanation of the model that seems "clear" is not necessarily stable when the distribution of data changes or when there is an inequality between current debtors and problematic debtors. These findings enrich the understanding that the validity of XAI must be assessed not only in terms of the readability of explanations, but also in terms of the consistency of explanations under changing data conditions.

From an organizational and institutional perspective, this study found that organizational readiness, data governance maturity, and regulatory pressure are important determinants of the success of XAI adoption [22]. These findings are highly consistent with the responsible AI governance literature which emphasizes that responsible AI implementation relies on structural, relational, and procedural practices throughout the AI lifecycle. At the national level, the relevance of these findings is even stronger because the OJK has launched Artificial Intelligence Governance for Indonesian Banks on April 29, 2025 and stated it as the minimum benchmark for the banking sector in developing and implementing AI responsibly [23]. The guidance complements the banking's existing digital transformation framework and emphasizes risk management and prudential principles. Thus, the results of this study are not only academically reasonable, but also in accordance with the actual regulatory developments in Indonesia: explainability is no longer just a design preference, but is starting to become a governance need [24].

The findings are also in line with the literature that places transparency and explainability as quality requirements in the development of AI systems. Balasubramaniam et al. point out that in organizational practice, explainability is treated as an integral part of transparency, with the main function being to build trust, aid auditability, clarify

the purpose of the system, the data used, the behavior of the model, its outputs, and its limitations [25]. This helps explain why in this study organizational readiness is not just a matter of the availability of computing or technical talent, but also a question of whether the organization has the ability to define the need for an explicit explanation. In other words, a mature organization asks not only "which model is the most accurate", but also "what kind of explanation is needed by risk analysts, regulators, and customers" [26].

The practical consequence of these findings is that XAI contributes to improving the quality of credit decisions in three dimensions at once: technical, ethical, and institutional. Technically, XAI helps analysts understand the main contributors to a risk score. Ethically, XAI opens up space to detect patterns of bias and injustice that were previously hidden behind the black-box model. Institutionally, XAI strengthens an organization's ability to conduct audits, documentation, and decision communication. Recent literature on the financial and credit sectors also confirms that explainability is directly related to fairness and the ability to reduce discriminatory decisions, especially when the model is used for critical activities. From a regulator's perspective, the BIS emphasized that a lack of explainability can increase risk models, complicate data quality assessments, hinder AI adoption, and pose a risk to consumer protection [27]. This means that the findings of this study have a broader contribution value than just increased interpretability; He pointed out that XAI can serve as a risk control mechanism in the digital banking ecosystem.

However, some results also show nuances that do not fully support the initial hypothesis. The research hypothesis that XAI will improve interpretability without significant consequences to performance is essentially supported, but with the caveat that increased clarity is not necessarily synonymous with increased operational simplicity. In certain contexts, the use of SHAP or LIME actually increases the computational burden, documentation needs, and interpretive competence of internal users [28]. Also, the fact that explanations are available doesn't automatically mean that all stakeholders will understand them well. This is where Miller's theory comes into play: effective explanations must be selective, contextual, and appropriate to the needs of the recipient. Thus, if the implementation of XAI fails to increase user trust optimally, the cause is not necessarily because the method is wrong, but it can be because the form of explanation provided is not in accordance with the capacity and needs of the end user.

Scientifically, the main contribution of this research lies in strengthening the argument that explainability in credit DSS should be understood as the result of the interaction between model design, data structure, and organizational governance. In other words, this study expands the discussion from the algorithmic level to the socio-technical level. XAI's literature in finance highlights a lot of methods and performance, while this study shows that the success of adoption in Indonesian digital banking is also determined by compatibility between business needs, regulatory expectations, and organizational maturity [16]. This contribution is important for the development of information systems science and technology management because it positions XAI not only as a model interpretation tool, but as a component of data-driven decision governance in digital organizations. [23]

This research also has some limitations. First, quantitative analysis focuses on a specific set of models and explainability techniques, so its generalization to all AI architectures is still limited. Second, the qualitative results are greatly influenced by the context of the institution interviewed, so they are analytical generalizations and not statistical representations of the entire Indonesian digital banking industry. Third, this study has not tested experimentally how customers or non-technical users actually understand the explanations produced by the model. This limitation is important because the study of explainability increasingly asserts that the quality of explanations must be measured not only from the algorithmic side, but also from the side of human acceptance and understanding. (Kostopoulos et al., 2024; Balasubramaniam et al., 2023; Miller, 2019)

Based on these limitations, further research is recommended to take four concrete directions. First, test a direct comparison between an inherently interpretable model and a post-hoc explainable model on Indonesia's digital banking data to assess the compromise between accuracy and accountability. Second, adding a fairness dimension more explicitly, for example by measuring the impact of the model on certain customer groups. Third, develop user-based experiments to assess whether the model's explanation actually improves the quality of analyst decisions or actually causes overreliance [29]. Fourth, expanding the analysis unit to aspects of AI governance across the lifecycle from design, validation, implementation, monitoring, to auditing to be more in line with the direction of OJK regulations and international supervisory practices that emphasize explainability as part of the risk management model.

4. Conclusion

This study shows that the adoption of Explainable Artificial Intelligence (XAI) in Decision Support Systems (DSS) in the credit scoring system in Indonesian digital banking is able to increase the interpretability and transparency of decisions without significantly sacrificing predictive performance. Hybrid models that combine a black-box approach with XAI techniques have proven to be effective in balancing model accuracy and clarity. In addition, the success of XAI implementation is not only determined by technical aspects, but also influenced by organizational readiness, compliance with OJK regulations, and data governance maturity. The implementation of XAI also has a positive impact on the quality of credit decisions, especially in increasing accountability, reducing potential bias, and strengthening user trust. Overall, the study confirms that XAI plays an important role in the development of a transparent and responsible DSS. However, further research is still needed to test the fairness aspect, evaluate users' understanding of the model explanation, and expand the context of implementation in various banking institutions.

References

- [1] N. M. M. Akbary, I. Trinugroho, T. Risfandy, and P. Pamungkas, "Digital transformation and efficiency: Evidence from Indonesian banks," *International Journal of Business and Society*, vol. 26, no. 1, 2025.
- [2] G. Kostopoulos, G. Davrazos, and S. Kotsiantis, "Explainable artificial intelligence-based decision support systems: A recent review," *Electronics*, vol. 13, no. 14, p. 2842, 2024. doi: 10.3390/electronics13142842
- [3] N. Thalpage, "Unlocking the black box: Explainable artificial intelligence (XAI) for trust and transparency in AI systems," *Journal of Digital Art and Humanities*, vol. 4, no. 1, pp. 31–36, 2023.
- [4] A. Ismail, R. Setiawati, H. Herbenita, B. Sutejo, and S. Mulyanto, *Management Information System: Practical Insights and Applications in Indonesia*. Asadel Publisher, 2024.
- [5] D. R. W. Napitupulu, "Regulatory challenges of digital banking supervision in Indonesia," *International Journal of Law Analysis*, vol. 4, no. 1, pp. 17–36, 2026.
- [6] D. V. Minh, H. X. Wang, Y. F. Li, and T. N. Nguyen, "Explainable artificial intelligence: A comprehensive review," *Artificial Intelligence Review*, vol. 55, no. 5, pp. 3503–3568, 2022. doi: 10.1007/s10462-021-10088-y
- [7] M.-S. Jameaba, "Digitalization, emerging technologies, and financial stability: Challenges and opportunities for the Indonesian banking industry," 2022. doi: 10.32388/CSTTYQ
- [8] W. I. Permata and H. Subiyantoro, "Digital banking transformation: Opportunities, challenges, and collaboration," *Greenation International Journal of Economics and Accounting*, vol. 3, no. 3, pp. 481–493, 2025.
- [9] W. Wipulanusat, K. Panuwatwanich, R. A. Stewart, and J. Sunkpho, "Applying mixed methods sequential explanatory design to innovation management," in *Proc. 10th Int. Conf. Engineering, Project, and Production Management*, Springer, 2020, pp. 485–495. doi: 10.1007/978-981-15-1910-9_40
- [10] M. A. S. Toyon, "Explanatory sequential design of mixed methods research: Phases and challenges," *International Journal of Research in Business and Social Science*, vol. 10, no. 5, pp. 253–260, 2021. doi: 10.20525/ijrbs.v10i5.1262
- [11] J. Schoonenboom, "The fundamental difference between qualitative and quantitative data in mixed methods research," *Forum Qualitative Sozialforschung*, vol. 24, no. 1, 2023. doi: 10.17169/fqs-24.1.3937
- [12] H. P. Kothandapani, "Leveraging AI for credit scoring and financial inclusion in emerging markets," *World Journal of Advanced Research and Reviews*, vol. 15, no. 3, pp. 526–539, 2022. doi: 10.30574/wjarr.2022.15.3.0732
- [13] A. K. M. Haque, "Explainable artificial intelligence (XAI): Making AI understandable for end users," 2025.
- [14] J. Černevičienė and A. Kabašinskas, "Explainable artificial intelligence (XAI) in finance: A systematic literature review," *Artificial Intelligence Review*, vol. 57, no. 8, 2024. doi: 10.1007/s10462-024-10854-8
- [15] A. Kovari, "AI for decision support: Balancing accuracy, transparency, and trust across sectors," *Information*, vol. 15, no. 11, p. 725, 2024. doi: 10.3390/info15110725
- [16] K. Coussement, M. Z. Abedin, M. Kraus, S. Maldonado, and K. Topuz, "Explainable AI for enhanced decision-making," *Decision Support Systems*, vol. 184, p. 114276, 2024. doi: 10.1016/j.dss.2024.114276
- [17] D. Hooshyar and Y. Yang, "Problems with SHAP and LIME in interpretable AI for education," *IEEE Access*, vol. 12, pp. 137472–137490, 2024. doi: 10.1109/ACCESS.2024.3470502
- [18] C. N. Nwafor, O. Nwafor, and S. Brahma, "Enhancing transparency and fairness in automated credit decisions," *Scientific Reports*, vol. 14, p. 25174, 2024. doi: 10.1038/s41598-024-75026-8
- [19] C. Rudin, "Stop explaining black box machine learning models for high stakes decisions," *Nature Machine Intelligence*, vol. 1, pp. 206–215, 2019. doi: 10.1038/s42256-019-0048-x
- [20] B. Somu, "Transforming customer experience in digital banking through machine learning," *International Journal of Engineering and Computer Science*, vol. 9, no. 12, 2020.
- [21] Y. Chen, R. Calabrese, and B. Martin-Barragan, "Interpretable machine learning for imbalanced credit scoring datasets," *European Journal of Operational Research*, vol. 312, no. 1, pp. 357–372, 2024. doi: 10.1016/j.ejor.2023.08.027
- [22] T. Tambun, G. Yudoko, and L. Aldianto, "Strategy and innovation in AI oversight: Fiduciary duties of banking boards," 2025.
- [23] Otoritas Jasa Keuangan, "Artificial Intelligence Governance for Indonesian Banks," Jakarta, 2025. [Online]. Available: <https://www.ojk.go.id>
- [24] E. Papagiannidis, P. Mikalef, and K. Conboy, "Responsible artificial intelligence governance," *Journal of Strategic Information Systems*, vol. 34, no. 2, p. 101885, 2025. doi: 10.1016/j.jsis.2024.101885
- [25] N. Balasubramaniam et al., "Transparency and explainability of AI systems," *Information and Software Technology*, vol. 159, p. 107197, 2023. doi: 10.1016/j.infsof.2023.107197
- [26] L. Putranti, R. D. Afriyanti, and A. Sumantika, "Which model is the most accurate?," *UPY Business and Management Journal*, vol. 5, no. 1, pp. 83–99, 2026.
- [27] M. M. Islam and M. M. Hasan, "Explainable AI models for cloud-based business intelligence," *American Journal of Interdisciplinary*

- Studies*, vol. 4, no. 3, pp. 208–249, 2023.
- [28] C. Norrie, “Explainable AI techniques for sepsis diagnosis,” 2021.
- [29] F. Pérez-Cruz, J. Prenio, F. Restoy, and J. Yong, “Managing explanations: How regulators can address AI explainability,” *BIS*, 2025.