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Artificial Intelligence Based Financial Digital Twin Framework for Credit Risk Monitoring in Banking Systems

Ni Luh Putu Nita Yulianti [1*], Yumiad Fernando Richard[1], Apolinaris S Awotkay[1], Kania Miftahul Jannah [1]
[1]Musamus Universty
Jalan Kamizaun Mopah Lama Merauke 99611. Indonesia
*Email Korespondensi: yuliantinita@unmus.ac.id[1]

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ABSTRACT

Artificial Intelligence (AI) and Financial Digital Twin (FDT) are emerging technologies with significant potential to enhance the effectiveness of credit risk monitoring in modern banking systems. This study aims to analyze research developments related to the application of AI and FDT in credit risk monitoring and to develop a conceptual framework for an AI-based Financial Digital Twin in banking systems. The study employs the Systematic Literature Review (SLR) method based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. Research data were obtained from 20 relevant scientific articles addressing AI, machine learning, XAI, digital twins, and banking risk management. The findings indicate that AI has become a key technology in credit risk assessment through the implementation of machine learning, deep learning, and predictive analytics, which improve the accuracy of credit risk prediction. Furthermore, XAI contributes to enhancing the transparency and interpretability of AI models in credit decision-making processes. This study proposes a conceptual framework consisting of a data input layer, AI analytics layer, Financial Digital Twin layer, predictive risk system, early warning system, and decision support system to support more adaptive, transparent, and proactive credit risk monitoring practices.

Kata kunci: Artificial Intelligence, Financial Digital Twin, Credit Risk, Banking, Explainable Artificial Intelligence

INTRODUCTION

The banking industry is undergoing rapid transformation driven by digitalization, intensifying competition, changing customer expectations, and increasing pressure for operational efficiency (Ismawanti et al., 2025). Technological developments such as Artificial Intelligence (AI), big data analytics, and financial technology (FinTech) have transformed the way financial institutions conduct operations and provide services to customers. Artificial Intelligence (AI) is a key driver of increased bank efficiency and profitability through service automation and intelligent financial systems. These changes are encouraging banking institutions to build faster, more adaptive, and data-driven decision-making systems (Kaya, 2019). The use of Artificial Intelligence (AI) in the banking sector can improve the quality of financial analysis, risk detection, and the effectiveness of digital services (Jain, 2023).

Credit risk management is a crucial aspect of banking operations. Credit risk is the possibility of a debtor failing to meet their financial obligations, which can impact a bank's stability and profitability. Traditional credit risk monitoring systems generally rely on historical evaluations and static credit scoring models, making them less able to detect changes in a customer's financial condition in real time (Noriega et al., 2023). Conventional approaches often struggle to identify complex and dynamic risk patterns in modern banking systems. The development of Artificial Intelligence (AI) offers new opportunities to improve the effectiveness of credit risk assessment and monitoring systems (Wei, 2023). Through machine learning and predictive analytics, AI can process large amounts of financial data, identify risk patterns, and predict potential defaults more accurately (Chang et al., 2025). Research (Machado et al., 2025)shows that machine learning models such as Random Forest can improve the effectiveness of early warning systems (EWS) and help banking institutions mitigate potential financial losses. The use of Artificial Intelligence (AI) supports faster, more efficient, and more data-driven credit decision-making (Noriega et al., 2023).

The development of Digital Twin technology is opening up new opportunities for developing real-time financial simulation and monitoring systems. A Financial Digital Twin (FDT) is a virtual representation of a customer's financial condition and banking operations, continuously updated using actual data. This technology enables financial behavior simulation, predictive analysis, and dynamic risk monitoring (Anshari et al., 2022). Artificial Intelligence (AI) -based Financial Digital Twins (FDTs) are capable of creating a more personalized, adaptive, and real-time financial services system (R. K. Para et al., 2025).

The combination of Artificial Intelligence (AI) and Financial Digital Twin (FDT) is seen as having great potential in building a smarter and more predictive credit risk monitoring system (Widagdo et al., 2023). In this approach, Artificial Intelligence (AI) plays a role in processing and analyzing customer financial data, while the Financial Digital Twin (FDT) provides real-time virtual simulations to model future credit risk conditions. The Financial Digital Twin (FDT) enables dynamic simulation of risk scenarios and financial system resilience (Acharya & Bhojak, 2025). The integration of these two technologies also supports the development of intelligent credit scoring, predictive risk monitoring, and a more effective early warning system (R. K. Para et al., 2025).

While research on Artificial Intelligence (AI) in the banking sector and credit risk assessment has advanced rapidly, research specifically integrating AI and Financial Digital Twins (FDTs) for credit risk monitoring in the banking system remains limited. Most research focuses on implementing AI or digital banking separately (Fares et al., 2023) While the development of a conceptual framework that integrates both technologies has not been discussed comprehensively (Jain, 2023). This limitation indicates a research gap that opens up opportunities for the development of a credit risk monitoring model based on integrating Artificial Intelligence (AI) -powered Financial Digital Twins in modern banking systems. This study aims to develop a conceptual framework for an Artificial Intelligence (AI) based Financial Digital Twin for credit risk monitoring in banking systems through a Systematic Literature Review (SLR) approach. This research is expected to provide theoretical contributions to the development of (F. Ahmed & Iqbal, 2025) Artificial Intelligence (AI) and Financial Digital Twin literature as well as practical contributions in the form of a conceptual model to support intelligent and sustainable banking systems in the future.

LITERATURE REVIEW

Artificial Intelligence in Banking Systems

Artificial intelligence (AI) is a branch of computer science that aims to enable machines or computers to perform tasks similar to those performed by humans, even with the same level of quality (Nurul Ilahi, 2024). In the banking sector, Artificial Intelligence (AI) has developed into one of the main technologies supporting digital transformation and increasing operational efficiency (Pradessa & Prasetio, 2025).

Artificial Intelligence (AI) has the ability to improve the quality of financial decision-making through predictive analytics and machine learning . This technology enables banks to identify customer transaction patterns, detect suspicious activity, and predict financial risks more effectively (Jain, 2023). In credit risk management, Artificial Intelligence (AI) is widely used to improve the effectiveness of credit scoring and early warning systems. Machine learning algorithms are capable of analyzing various debtor financial variables in a more complex way than traditional statistical models. (Noriega et al., 2023). Artificial Intelligence (AI) has become a key driver of strategic transformation in credit risk management in commercial banks through faster, more adaptive, and predictive data analysis (Bi & Bao, 2024).

The implementation of Artificial Intelligence (AI) in the banking system is characterized by its often black-box nature, making it difficult for regulators and policymakers to understand (Guan et al., 2023). Transparency, fairness, and accountability are crucial aspects in the development of AI for the financial sector. Therefore, the concept of Explainable Artificial Intelligence (XAI) has been developed to increase trust in Artificial Intelligence (AI) systems and ensure that credit decisions can be accounted for more transparently (Chang et al., 2025). Various studies have shown that Artificial Intelligence (AI) plays a crucial role in supporting the transformation of the modern banking system, particularly in improving the effectiveness of credit risk monitoring, predictive analytics , and data-driven decision-making. The development of Artificial Intelligence (AI) technology also opens up opportunities for integration with other technologies, such as the Financial Digital Twin (FDT), to create a smarter, more adaptive, and more sustainable banking system.

Financial Digital Twin (FDT)

Digital Twin technology initially developed in the manufacturing and engineering sectors as a virtual representation of a physical object or system that is continuously updated using real-time data. As digital transformation progressed, the concept began to be applied in the financial sector, giving rise to the concept of Financial Digital Twin (FDT) (Chursin et al., 2024). A Financial Digital Twin (FDT) is a virtual simulation of a customer's financial condition, credit system, and banking operations, designed to create dynamic financial monitoring and analysis (Anshari et al., 2022).

Financial Digital Twin (FDT) enables financial institutions to build hyper-personalized finance service systems through real-time data integration, Predictive analytics and artificial intelligence (Saddik et al., 2021). This technology can virtually represent customer financial behavior, enabling banks to simulate financial conditions, analyze risks, and make more adaptive decisions. Financial Digital Twins (FDTs) also support the development of a financial system that is more responsive to economic changes and market behavior. (R. K. Para et al., 2025) The Financial Digital Twin (FDT) concept can be used to build systemic risk simulations in the FinTech and modern banking ecosystems. Through a cybernetic digital twin approach, the system can predict potential financial crises and simulate various risk scenarios in real time. This approach helps financial institutions increase systemic resilience and strengthen financial risk mitigation strategies (Acharya & Bhojak, 2025).

The combination of Artificial Intelligence (AI) with the Financial Digital Twin (FDT) enables the development of more sophisticated simulation-based risk management. This technology utilizes predictive analytics, Monte Carlo simulations, and agent-based modeling to more accurately predict potential credit risk and economic volatility. Thus, the Financial Digital Twin (FDT) functions not only as a monitoring system but also as a predictive simulation tool to support financial decision-making. (Pattabhi, 2025)The development of Financial Digital Twins (FDTs) demonstrates the technology's significant potential for creating a smarter, more real-time, and more adaptive banking system. The integration of virtual simulations and Artificial Intelligence (AI) enables banking institutions to build more accurate credit risk monitoring and supports the development of a future intelligent banking ecosystem.

Credit Risk Monitoring

Credit risk monitoring is the process of identifying, measuring, evaluating, and controlling the risks arising from the potential failure of a debtor to fulfill its financial obligations (Chen, 2024). Credit risk is one of the main risks in the banking system because it can affect a bank's asset quality, profitability, and financial stability (Aryani & Assegaf, 2026). Therefore, banking institutions require an effective monitoring system to reduce the potential for non -performing loans (NPLs) (Toprak & Eke, 2020). Traditional credit risk monitoring approaches generally rely on historical evaluations, periodic financial reports, and static credit scoring models. These approaches are limited in identifying dynamic changes in customer financial behavior (Arora & Kaur, 2026). Advances in machine learning technology provide new opportunities to improve the effectiveness of credit risk monitoring through predictive analytics and real-time data analysis (Noriega et al., 2023).

A machine learning-based Early Warning System (EWS) is used to predict credit risk in commercial customers. The research shows that the AI system can detect potential risks early and help banks significantly reduce financial losses. The research also explains that (I. E. Ahmed et al., 2023) the Adaptive Neural Network-Based Fuzzy Inference System (ANFIS) model is effective in determining banking risk indices based on various financial indicators (Machado et al., 2025). Artificial Intelligence (AI) has become a crucial part of transforming credit risk monitoring systems in modern banks. The use of predictive analytics enables banking institutions to analyze debtor behavior, evaluate transaction patterns, and monitor credit quality more quickly and accurately. Therefore, AI- based credit risk monitoring can improve decision-making effectiveness and strengthen banking risk mitigation systems (Bi & Bao, 2024).

Explainable and *Responsible Artificial Intelligence*

The development of Artificial Intelligence (AI) in the banking system not only presents opportunities but also raises challenges related to transparency, fairness, and accountability in decision-making. Many machine learning models have black-box characteristics, making them difficult to explain to regulators and customers. This condition is a significant concern in the financial sector because credit decisions must be objectively and transparently accounted for. Explainable Artificial Intelligence (XAI) is an important approach to improving the interpretability of Artificial Intelligence (AI) models in credit risk assessment. Explainable Artificial Intelligence (XAI) enables banking institutions to understand the factors that influence credit decisions, thereby increasing trust in Artificial Intelligence (AI) systems. The use of model interpretation techniques also helps regulators oversee Artificial Intelligence (AI) -based credit decisions (Chang et al., 2025), explaining that.

Responsible Artificial Intelligence (AI) in credit risk assessment systems. This research combines machine learning with human knowledge acquisition to improve the fairness and accountability of credit decisions. This approach demonstrates that integrating human intelligence and AI can help reduce algorithmic bias and improve the quality of financial decision-making. (Guan et al., 2023). The use of Generative AI and Explainable AI can strengthen real-time credit risk modeling systems. This technology helps financial institutions increase the transparency of data analysis while strengthening the security of digital financial systems. Therefore, the implementation of Explainable and Responsible AI is a crucial aspect in the development of a sustainable, intelligent banking system (Townsend, 2023).

RESEARCH METHOD

This study uses a qualitative approach with the Systematic Literature Review (SLR) method (Haddaway et al., 2022). The SLR method is used to identify, evaluate, and synthesize various previous studies related to Artificial Intelligence (AI) and Financial Digital Twin (FDT), credit risk monitoring, and digital transformation in the banking system. This approach was chosen because it is able to provide a systematic and comprehensive understanding of research developments in related fields and helps identify research gaps that are still open to development. This study also uses a conceptual approach to develop a conceptual framework for Financial Digital Twin (FDT) based on Artificial Intelligence (AI) in credit risk monitoring in the banking system. The framework development is carried out based on the results of literature synthesis obtained from various relevant studies. The literature selection process is carried out using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) approach. The selection stages consist of identification, screening, eligibility, and included studies.

Table 1Inclusion and Exclusion Criteria

Inclusion Criteria	Exclusion Criteria
Articles published in the period 2018–2026.	Articles that do not discuss the banking, finance, or financial technology sectors.
The article uses English.	Articles that are not relevant to credit risk monitoring or banking risk management.
Articles come from international journals or peer reviewed conference proceedings.	Duplicate articles found in more than one database.
The article discusses the topics of Artificial Intelligence, Financial Digital Twin, digital banking, or credit risk monitoring in the banking sector.	Non-peer-reviewed articles, editorials, or non-scientific opinions.

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The article has relevance to predictive analytics, intelligent financial systems, or credit risk assessment.	Articles with discussions that are too general and do not support the research focus.

In the identification stage, researchers collected articles from various international databases using predetermined keywords. Next, in the screening stage, they were screened based on the title, abstract, and keywords to identify the research's relevance to the topics of Artificial Intelligence, Financial Digital Twins , and credit risk monitoring. The eligibility stage involved reading the full text of the articles to ensure the content aligned with the study's focus. Articles that did not address AI integration, banking systems, or credit risk monitoring were excluded from the selection process. After completing all stages, 20 primary articles were selected, which were used in the literature synthesis process and the development of the research's conceptual framework.

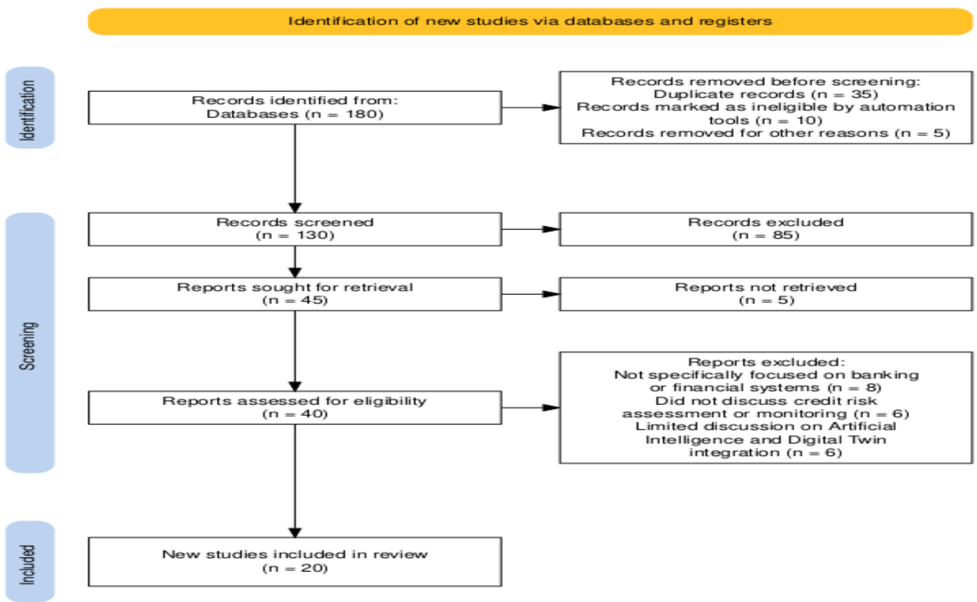

Figure 1Prism Diagram

RESULTS

Artificial Intelligence and Financial Digital Twin Research Trends

Based on the results of *the Systematic Literature Review* (SLR), 20 main articles were obtained which were analyzed thematically based on research focus, methods, and main findings related to *Artificial Intelligence* (AI), *Financial Digital Twin* (FDT), and credit risk monitoring in the banking system.

Table 2Research Literature Synthesis

No	Author & Year	Research Title	Research Focus	Method	Findings
1	(Anshari et al., 2022)	Digital Twin: Financial Technology's Next Frontier of	Exploring the concept of a robo-advisor with digital twin (DT) capabilities for personal	An exploratory study with thematic analysis of current literature to develop an	DT integration into robo-advisors enables more dynamic, personalized

No	Author & Year	Research Title	Research Focus	Method	Findings
		Robo-Advisors	financial management.	interactive and interpretive model.	financial advisory services and adds value to users' financial well-being.
2	(Fares et al., 2023)	Utilization of artificial intelligence in the banking sector: a systematic literature review	Systematically reviewing the use of AI in the banking sector since 2005.	Systematic Literature Review (SLR) of 44 articles using content and thematic analysis and Leximancer software .	Identifying three key areas of AI research in banking: Strategy, Process, and Customer. AI has been shown to improve operational efficiency and customer experience through chatbots and robo-advisory systems .
3	(Jain, 2023)	Role of artificial intelligence in banking and finance	Analyzing the role of AI in revolutionizing the banking and finance industry, particularly in fraud detection and credit scoring.	An in-depth literature review (qualitative analysis) of various AI applications in the financial sector.	AI significantly improves decision-making processes, reduces operational costs, and increases profitability, although data privacy and ethical challenges remain.
4	(Rich, 2019)	Artificial intelligence in banking: A lever for profitability with limited implementation to date	Analyzing the potential of AI as a driver of bank profitability and the current status of its implementation.	Economic and market analysis using venture capital investment data and global AI patent trends.	The implementation of AI in banks is still in its early stages (modest) but has great potential to reduce costs by increasing workforce productivity and bank ROA.
5	(RK Para et al., 2025)	AI-Powered Financial Digital	Exploring the use of Financial Digital Twins	System architecture analysis (5	FDTs go beyond traditional analytics by

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No	Author & Year	Research Title	Research Focus	Method	Findings
		Twins: The Next Frontier in Hyper-Personalized, Customer-Centric Financial Services	(FDTs) to create hyper-personalized financial services .	layers: data fabric , behavioral models, simulation, decision intelligence, and experience orchestration).	replicating customer behavior in real time. Their implementation requires edge AI infrastructure and confidential computing for data security.
6	(Stratopoulos & Wang, 2025)	Artificial intelligence and accounting research: a framework and agenda	Proposes a framework for classifying AI research in accounting.	Development of a two-dimensional framework: research focus (accounting vs AI) and methodological approach (AI-based vs traditional).	AI is transformative for accounting research. This framework helps researchers navigate collaboration opportunities between accounting experts and computer scientists.
7	(Noriega et al., 2023)	Machine Learning for Credit Risk Prediction: A Systematic Literature Review	Reviewing the use of Machine Learning (ML) for credit risk prediction in the microfinance industry.	Systematic Literature Review (SLR) of 52 relevant studies in the field of computer science and finance.	Boosted category algorithm is the most researched. Key challenges include black-box models , the need for explainable AI (XAI), and data imbalance.
8	(Chang et al., 2025)	Prediction of bank credit worthiness through credit risk analysis: an explainable machine learning study	Improving AI transparency in creditworthiness assessment in supply chain finance .	Comparison of various ML algorithms (Random Forest, Gradient Boosting, etc.) and application of XAI techniques for feature ranking.	Gradient Boosting proved to be the best-performing algorithm. This study successfully identified key features influencing credit decisions, making them more transparent to policymakers.

No	Author & Year	Research Title	Research Focus	Method	Findings
9	(Machado et al., 2025)	An analytical approach to credit risk assessment using machine learning models	Developing an ML-based Early Warning System to monitor commercial customer credit risk.	A case study on a Dutch international bank using various models (SVM, RF, ANN, etc.) and SHAP values for interpretation.	Random Forest delivered the highest performance (best F1-score). This system was able to anticipate 12.7% of negative customer transitions and prevent 67.6% of potential bank financial losses.
10	(Guan et al., 2023)	Responsible Credit Risk Assessment with Machine Learning and Knowledge Acquisition	Investigating the use of human expertise to improve data limitations in responsible credit risk assessment.	Combining ML models (XGBoost) with human knowledge acquisition through the Ripple-Down Rules (RDR) method.	The combined model (ML+RDR) provides performance equivalent to models trained on large datasets and improves the fairness and accountability of credit decisions.
11	(Acharya & Bhojak, 2025)	Financial Doppelgangers: a cybernetic novel Digital-Twin framework...	Digital Twin framework for systemic resilience in the FinTech ecosystem.	Development of a cybernetics-based conceptual framework.	Financial Doppelgangers enables real-time simulation of crisis scenarios to predict and mitigate systemic risks before they occur.
12	(Broby, 2021)	Financial technology and the future of banking	Analyzing the impact of FinTech innovation on traditional banking business models.	Theoretical analysis based on classical banking theory and digital transformation.	Banks must choose a strategy between customer retention, acquisition, Banking-as-a-Service , or social media payment platforms to survive the

No	Author & Year	Research Title	Research Focus	Method	Findings
					threat of shadow banking.
13	(Papathomas & Konteos, 2024)	Financial institutions digital transformation: the stages of the journey...	Identifying the phases of digital transformation in incumbent banks and their measurement metrics.	General literature review and field observations.	The digital transformation of banking consists of three main phases with specific tracking indicators (KPIs) to ensure progress from traditional to digital banking.
14	(IE Ahmed et al., 2023)	The role of artificial intelligence in developing a banking risk index...	Developing a bank risk rating index using a neuro-fuzzy system (ANFIS).	Quantitative (ANFIS and Mahalanobis Distance) using data from 45 banks in the Gulf countries (Gulf banks).	The ANFIS model effectively determines the risk ratios that most influence a bank's financial stability, providing guidance for regulators and managers.
15	(Pattabhi, 2025)	Financial Digital Twins: AI and Simulation-Based Risk Management.	Reviewing the use of Financial Digital Twins (FDTs) for risk management and fraud detection.	Literature review on AI and simulation models	FDTs that combine AI with Monte Carlo simulation or Agent-Based Modeling are crucial in anticipating risks amidst global economic volatility.
16	(Kuanova & Otegen, 2026)	Artificial Intelligence in Banking Risk Management: A Bibliometric Analysis	Mapping global publication trends and thematic structure of AI in banking risk management.	Bibliometric analysis of 83 articles from Web of Science (2020-2024).	Research interest grew by 41.4%. Key clusters include AI-based credit risk assessment, fraud detection, and regulatory compliance.
17	(Townsend, 2023)	Explainable Generative AI-Enhanced Credit and Threat Risk Modeling..	Proposes a real-time cloud architecture that integrates Generative AI with Explainable AI (XAI).	Technical architecture development (Apache-SAP HANA) and case studies.	The use of GANs/VAEs can strengthen limited borrower data, while XAI ensures that AI decisions can be

No	Author & Year	Research Title	Research Focus	Method	Findings
					transparently accounted for.
18	(Bi & Bao, 2024)	Innovative Application of Artificial Intelligence Technology in Bank Credit Risk Management	Exploring how AI improves credit decision-making mechanisms in commercial banks.	Descriptive analysis and review of AI technology applications.	AI is becoming a key driver of banks' strategic transformation, improving the accuracy of credit decisions and scientifically maintaining asset quality security.
19	(Arora & Kaur, 2026)	The confluence of artificial intelligence and credit risk assessment ...	Conducting a comprehensive scientometric analysis of AI in credit risk assessment.	Scientometric analysis of 2,151 articles (2000-2025).	Research has expanded from the consumer to the corporate domain, with a strong emphasis on more sophisticated methodological stages in P2P lending and banking.
20	(Wang et al., 2024)	Digitalization as a double-edged sword: A deep learning analysis...	Analyzing the impact of digitalization on the risk-taking behavior of banks in China.	Quantitative using deep learning models (InstructGPT-inspired) on 149 banks.	on-balance sheet risk but simultaneously increases off - balance sheet risk exposure .

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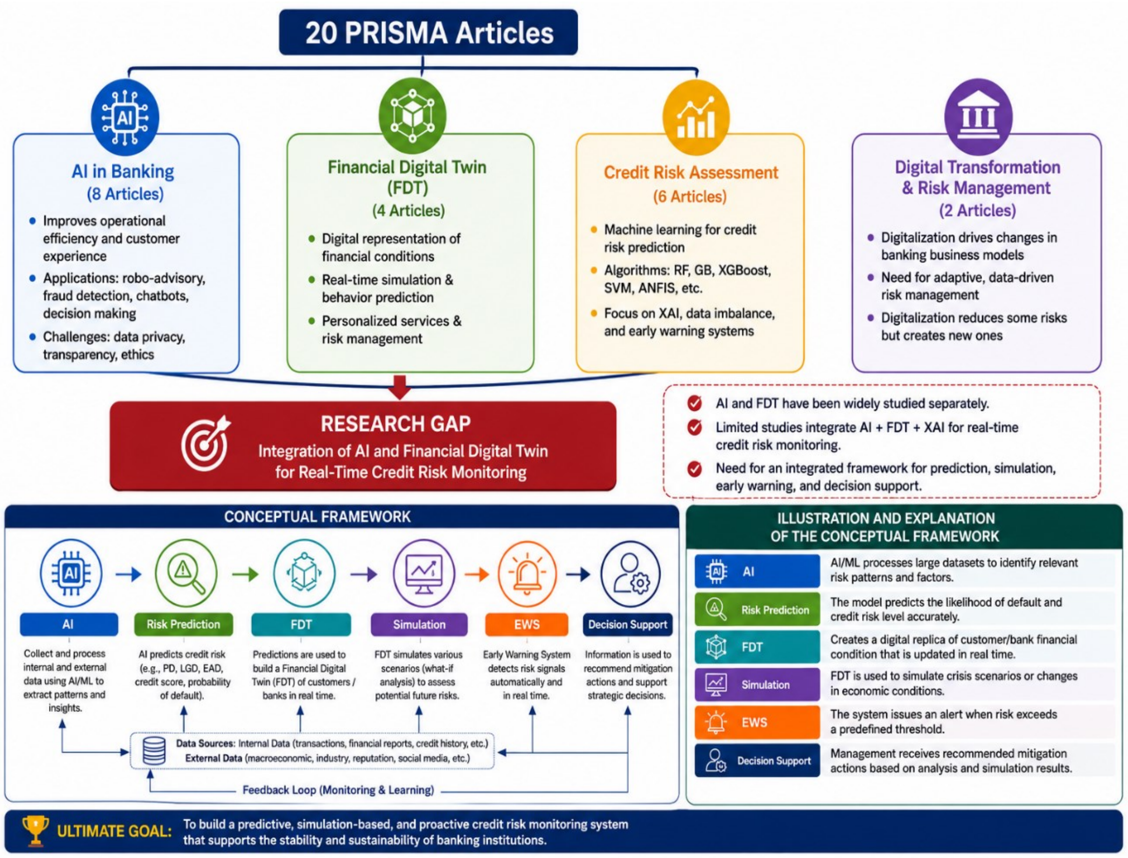

Figure 2 Proposed Conceptual Framework of Artificial Intelligence-Based Financial Digital Twin for Real-Time Credit Risk Monitoring in Banking Systems

DISCUSSION

Thematic Analysis of Research Trends:

The synthesis of 20 articles shows several key trends in Artificial Intelligence and Financial Digital Twin research in the banking sector. Most research indicates that Artificial Intelligence is a key technology in developing credit risk assessments. Models such as Random Forest, Gradient Boosting, ANFIS , and deep learning have been shown to improve the accuracy of credit risk predictions compared to conventional methods (Chang et al., 2025). Machine learning is also used in the development of Early Warning Systems (EWS) , which can detect changes in customer conditions more responsively (Machado et al., 2025).

The development of Artificial Intelligence (AI) applications in the banking sector presents both opportunities and challenges. One major challenge is the low transparency of AI models, known as the black-box problem , which makes the credit decision-making process difficult to explain. To address this, the Explainable Artificial Intelligence (XAI) and Responsible AI approaches have been developed, emphasizing transparency, accountability, fairness, and trust in the use of AI (Townsend, 2023). Financial Digital Twins are emerging as a new approach in modern financial systems. This technology enables the creation of real-time digital representations of financial conditions, allowing them to simulate customer behavior, analyze various risk scenarios, and evaluate the impact of changing economic conditions (Noriega et al., 2023). This development represents a shift from static risk analysis to a more dynamic, simulation-based approach.

Digital transformation also increases banking operational efficiency, but at the same time increases risk complexity (Papathomas & Konteos, 2024). Overall, research trends point to the combination of AI and Financial Digital Twins to support real-time risk monitoring, predictive analytics, and simulation-based decision-making in realizing an intelligent banking ecosystem. (Acharya & Bhojak, 2025).

The Role of Artificial Intelligence in Credit Risk Monitoring
Artificial Intelligence plays an increasingly dominant role in modern credit risk monitoring systems through its capabilities for large-scale data analysis, complex pattern identification, and real-time risk prediction (R. Para et al., 2025). Various studies have shown that machine learning algorithms such as Random Forest, Gradient Boosting, ANFIS , and neural networks significantly improve credit scoring accuracy compared to traditional approaches (Chang et al., 2025). Among these approaches, ensemble models such as Random Forest and Gradient Boosting are widely reported to have more stable performance in detecting non-performing credit risks. In addition to improving accuracy, AI is also widely applied in the development of Early Warning Systems (EWS). fraud detection, and risk classification that enable banking institutions to mitigate risks more proactively (Machado et al., 2025).

Part Most AI models in the banking system still face the major challenge of limited transparency due to their black-box nature. Therefore, an Explainable Artificial Intelligence (XAI) approach is becoming increasingly important in ensuring that credit decisions can be explained, audited, and accounted for (Townsend, 2023).

The Role of Financial Digital Twin in Banking Systems
Financial Digital Twin (FDT) is a virtual representation of financial conditions that is continuously updated using real-time data, thus enabling the financial system to perform simulations and analyses dynamically. Based on the results of literature synthesis (Anshari et al., 2022; Para et al., 2025)and (Pattabhi, 2025)FDT has several main functions, namely: Real-Time Simulation of Customer Financial Conditions, Risk Scenario Analysis in Various Economic Conditions, Modeling Financial Behavior and Customer Interactions and Detection of Potential Systemic Risks at the Institutional and Ecosystem Levels.

The Financial Digital Twin (FDT) also supports the development of more personalized financial services through the concept of hyper-personalized finance (Saddik et al., 2021), where financial decisions can be adaptively tailored to individual circumstances. Thus, the Financial Digital Twin serves not only as a monitoring tool but also as a predictive simulation system that supports strategic decision-making in modern banking systems.

Combination of Artificial Intelligence and Financial Digital Twin for Credit Risk Monitoring
The combination of Artificial Intelligence (AI) and Financial Digital Twin (FDT) represents a further development in credit risk monitoring systems, leading to a more adaptive, predictive, and real-time simulation-based approach (R. Para et al., 2025). The results of literature synthesis indicate that these two technologies have complementary functions in building a smarter banking system. Artificial Intelligence (AI) acts as an analytical engine tasked with processing large amounts of data, identifying risk patterns, and generating default probability predictions through machine learning and deep learning methods (Chang et al., 2025). Meanwhile, the Financial Digital Twin (FDT) functions as a virtual simulation environment that represents the financial condition of customers and banking institutions dynamically and is continuously updated based on real-time data

Research (R. K. Para et al., 2025) shows that the combination of Artificial Intelligence (AI) and Financial Digital Twin (FDT) enables the creation of a financial system capable of simultaneously performing predictive analysis and simulating customer behavior. This empowers banking institutions to not only understand current financial conditions but also project future changes based on various economic scenarios. Furthermore, (Acharya & Bhojak, 2025)it emphasizes that the digital twin approach in the financial system enables real-time simulation of systemic risk. With the combination of Artificial Intelligence (AI), the simulation becomes more intelligent because it can adjust risk parameters based on actual data patterns, thereby increasing the accuracy in detecting potential financial crises and defaults. Furthermore , (Pattabhi, 2025) it explains that the combination of Artificial Intelligence (AI) and Financial Digital Twin (FDT) strengthens simulation-based risk management capabilities through approaches such as Monte Carlo simulation and agent-based modeling. This integration enables the banking system to virtually test various risk scenarios before credit decisions are made, thus minimizing financial risk more effectively. Artificial Intelligence (AI) and Financial Digital Twin (FDT) result in a paradigm shift in credit risk management, from a reactive, historical-based system to a proactive, predictive, and real-time simulation-based system. This change also supports the development of an intelligent banking ecosystem that can adapt to economic dynamics and customer behavior more quickly.

The literature review also shows that the combination of Artificial Intelligence (AI) and Financial Digital Twin (FDT) is still in its early stages of development. Most research remains conceptual, and few have implemented it in real banking systems end-to-end. This suggests an opportunity for further research to develop a data-driven implementation model for the real banking industry. Therefore, the combination of Artificial Intelligence (AI) and Financial Digital Twin (FDT) can be positioned as a key foundation for developing a next-generation credit risk monitoring system that is more intelligent, adaptive, and sustainable.

Proposed Conceptual Framework

Based on the results of the literature synthesis on Artificial Intelligence (AI), Financial Digital Twin (FDT), and credit risk monitoring, this study proposes an integrative conceptual framework that combines the analytical capabilities of Artificial Intelligence (AI) with the real-time simulation capabilities of Artificial Intelligence (AI) and Financial Digital Twin (FDT) in a single intelligent banking system-based credit risk monitoring system. This framework is built to address the limitations of the traditional banking system, which is still static and reactive in managing credit risk, as well as the limitations of Artificial Intelligence (AI) models that have not been fully integrated with dynamic simulation mechanisms based on digital twins. The proposed conceptual framework is built through six main components that are integrated with each other in a continuous system flow. The process begins at the Data Input Layer, which is the stage of collecting data originating from various sources, such as customer transaction data, credit history, financial behavior, and macroeconomic indicators. All of this data serves as the basis for the process of identifying and analyzing credit risk. Next, the collected data is processed in the Artificial Intelligence Analytics Layer. At this stage, Artificial Intelligence (AI) technology is utilized through the application of machine learning and deep learning to perform data preprocessing, feature extraction, credit scoring, and predict the possibility of default. The result of this process is a predictive model that is able to describe the level of credit risk based on historical and current data.

The next stage is the Financial Digital Twin Layer, which builds a virtual representation of a customer's financial condition and the bank's credit portfolio. This digital model is updated in real time to reflect dynamic changes in financial conditions. Through this approach, the system can simulate customer financial behavior, project various future

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economic conditions, and evaluate the impact of changes in financial variables on credit risk levels. The integration of AI analysis results and simulations generated by the Financial Digital Twin occurs in the Integration Layer (AI–FDT Fusion System). In this layer, AI-generated risk predictions are combined with dynamic simulations from the Financial Digital Twin, resulting in predictive analysis based on various scenarios. This approach enables the system to provide a more comprehensive picture of risk than conventional method.

The results of this integration are then utilized in the Early Warning System (EWS) to detect potential increases in credit risk early. This early warning system enables banks to take necessary mitigation measures before the risk develops into non-performing loans or default. Finally, the resulting information is used in the Decision Support System as a basis for decision-making. This system supports various strategic decisions, from credit approvals and credit limit adjustments to developing more precise, adaptive, and data-driven risk mitigation strategies.

Illustration and Explanation of the Conceptual Framework

AI → Risk Prediction → FDT → Simulation → EWS → Decision Support

The proposed conceptual framework demonstrates that the credit risk monitoring process in the modern banking system is no longer linear, but rather has evolved into an integrative, dynamic, and cyclical system. Within this framework, Artificial Intelligence (AI) serves as the primary analytical engine capable of generating data-driven risk predictions through predictive analytics . The analysis results are then validated and enriched using the Financial Digital Twin (FDT) approach, which enables real-time and continuous simulation of customer financial conditions. The combination of Artificial Intelligence (AI) and the Financial Digital Twin (FDT) results in a credit risk monitoring system that is more adaptive to data changes, has a higher level of precision in predicting risks, is more responsive through the implementation of an Early Warning System (EWS), and is able to support decision-making based on various simulation scenarios. Thus, this framework represents the evolution of the banking system from a traditional approach that relies solely on historical data to an intelligent system based on Artificial Intelligence (AI) and the Financial Digital Twin (FDT) that is predictive, simulative, and adaptive to the dynamics of economic conditions and customer behavior.

This conceptual framework also contributes in three key aspects. From a theoretical perspective, this study expands the literature by integrating the concepts of Artificial Intelligence (AI) and Financial Digital Twin (FDT) into a single credit risk monitoring model, a concept rarely discussed comprehensively in previous research. From a methodological perspective, this study offers a novel approach by combining Artificial Intelligence (AI) -based predictive analytics with Financial Digital Twin (FDT) -based simulation-based modeling into a single, integrated credit risk analysis system. Meanwhile, from a practical perspective, this framework can serve as an implementation model for banks and financial institutions in building smarter, real-time, efficient, and adaptive credit risk monitoring systems to support risk management in the digital banking era.

Research Gap and Future Research

The literature synthesis results show that research on Artificial Intelligence (AI), Financial Digital Twins (FDTs) , and credit risk monitoring has experienced quite rapid development in recent years. However, the integration of these three aspects is still in its early stages of development and has not been widely implemented comprehensively in modern banking systems. Based on the results of the literature review, several major research gaps were identified. First, there is still a lack of research that comprehensively integrates Artificial Intelligence (AI) and Financial Digital Twins (FDTs) , as most studies only focus on them separately. Second, existing research is still dominated by conceptual approaches rather than empirical implementation, resulting in many models not being tested in real banking environments. Third, there is still a limited availability of end-to-end credit risk monitoring systems capable of integrating input data, Artificial Intelligence (AI) analysis , Financial Digital Twin (FDT) simulations , and decision support systems within a single integrated framework. Fourth, most research still uses simulated data or limited datasets, resulting in a lack of validation using real banking industry data.

Based on these research gaps, several opportunities for future research development exist. Further research could focus on implementing Artificial Intelligence (AI) and Financial Digital Twin (FDT) models in real-world banking systems to test the framework's effectiveness under real-world operational conditions. Furthermore, testing using large-scale banking industry datasets is also needed to improve the model's validity and reliability. Integrating other supporting technologies, such as blockchain and big data analytics, could be a potential research direction to improve security, transparency, and data processing capacity in credit risk monitoring. Developing a real-time, cloud-based intelligent banking system also presents a significant opportunity to support a more adaptive and efficient digital banking system. Furthermore, a comparative study between traditional AI models and hybrid systems based on Artificial Intelligence (AI) and Financial Digital Twin (FDT) is needed to determine the effectiveness, predictive accuracy, and risk mitigation capabilities of each approach.

CONCLUSION

This research aims to develop a conceptual framework for Financial Digital Twin (FDT) based on Artificial Intelligence. (AI) in credit risk monitoring in the banking system through the Systematic Literature Review (SLR) approach. Based on the analysis of 20 relevant articles, several main points can be concluded. First, Research developments show that Artificial Intelligence (AI) is becoming a dominant technology in the modern banking system, especially in credit scoring, risk prediction, and Early Warning System (EWS). Machine learning models such as Random Forest, Gradient Boosting, ANFIS, and deep learning have been proven to be able to increase the accuracy of credit risk predictions compared to conventional methods. Second, The results of the study show that the Financial Digital Twin (FDT) is starting to develop as a new paradigm in the financial system, which allows for real-time representation of financial conditions, customer behavior simulation, and dynamic risk scenario analysis. The Financial Digital Twin (FDT) not only functions as a monitoring tool, but also as a predictive simulation system in financial decision making. Third, the combination of Artificial Intelligence (AI) and Financial Digital Twin (FDT) offers significant potential for transforming credit risk monitoring systems, with Artificial Intelligence (AI) acting as the analytical engine and Financial Digital Twin (FDT) as the simulation environment. This combination creates a more adaptive, predictive, and real-time data-driven system that supports credit decision-making. Fourth, This research produces a conceptual framework of Artificial Intelligence (AI) and Financial Digital Twin (FDT) for credit risk monitoring, which consists of several main components, namely the data input layer, AI analytics layer, Financial Digital Twin layer, predictive risk system, Early Warning System (EWS), and decision support system. This framework shows a paradigm shift from a reactive credit risk monitoring system to a proactive and simulation-based system. Fifth, it was found that there is still a significant research gap, especially related to the lack of research that integrates Artificial Intelligence (AI) and Financial Digital Twin (FDT) end -to- end in a real banking system. Most of the research is still conceptual and not much has been tested empirically.

Based on the research findings, several suggestions can be provided for future study development and implementation. Theoretically, further research is recommended to expand the study of the combination of Artificial Intelligence (AI) and Financial Digital Twin (FDT) in the development of intelligent banking systems by building a more comprehensive conceptual model. This model needs to accommodate aspects of technology, risk management, and customer behavior in an integrated manner to be able to explain the dynamics of credit risk management more comprehensively. Practically, banking and financial institutions can utilize the resulting conceptual framework as a basis for developing intelligent technology-based credit risk monitoring systems to improve credit scoring accuracy, accelerate risk detection, and reduce the level of non-performing loans. For further research, empirical implementation using real banking data is needed to test the effectiveness of the proposed model. In addition, the integration of big data, cloud computing, and blockchain should be considered to improve analytical capabilities, security, transparency, and system reliability in various global banking contexts.

LIMITATION

This study has several limitations. First, the study used a Systematic Literature Review (SLR) method, so the results are still based on literature synthesis and have not been empirically tested using real banking data. Second, the study only included 20 articles that met the selection criteria, so there may still be relevant research that has not been accommodated. Third, the study focused on developing a conceptual framework for the combination of Artificial Intelligence (AI) and Financial Digital Twin (FDT) without testing the model's effectiveness in banking practice. Furthermore, aspects of technical implementation, data security, privacy, and the characteristics of Indonesian banking have not been discussed in depth.

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ABOUT THE AUTHOR(S)

1st Author
Ni Luh Putu Nita Yulianti is affiliated with the Department of Management, Faculty of Economics and Business, Musamus University, Merauke. She currently works as a lecturer at Musamus University, Merauke. Her research interests include Financial Management.
Email: yuliantinita@unmus.ac.id
ID ORCID: https://orcid.org/0009-0007-5239-3503

2rd Author
Yumiad Fernando Richard is affiliated with the Department of Management, Faculty of Economics and Business, Musamus University, Merauke. He currently serves as

a lecturer at Musamus University. His research interests include Financial Management.
Email: yumiadfernandoricard@unmus.ac.id
ID ORCID: https://orcid.org/0000-0002-0324-6570

3th Author
Apolinaris S. Awotkay is affiliated with the Department of Management, Faculty of Economics and Business, Musamus University, Merauke. He currently serves as a lecturer at Musamus University, Merauke. His research interests include Financial Management.
Email: apolinarisaworkay@unmus.ac.id

4th Author
Kania Miftahul Jannah is affiliated with the Department of Management, Faculty of Economics and Business, Musamus University, Merauke. She is currently a management student at Musamus University. Her research interests include Human Resource Management.
Email: kaniamiftahulj2002@gmail.com