At Turots: Jurnal Pendidikan Islam

Vol. 8, No. 1, Juni 2026, pp. 575-583
Print ISSN : 2656-7555 || Online ISSN : 2747-089X
http://journal.stitmadani.ac.id/index.php/JPI/index

A Data-Based Information System for Credit Risk Management in Banking Education

Roby Romadany [a.1], **Fajar Santoso** [b.2], **Bhenu Artha** [c.3,*]

[a] Universitas Pamulang, Indonesia
[b] UIN Raden Mas Said Surakarta, Indonesia
[c] Universitas Widya Mataram, Indonesia
[1] robyromadany.unpam@gmail.com; [2] fajar.santoso@staff.uinsaid.ac.id; *[3] bhenoz27@gmail.com
*Correspondent Author

Received: 13-02-2026 *Revised: 23-04-2026* *Accepted: 14-05-2026*

KEYWORDS

Credit risk;
Banking education;
Data-based information;
Design-based approach.

ABSTRACT

This study designs, implements, and validates a high-fidelity Data-Based Information System for Credit Risk Management (CRIS) as an educational simulation to close the mismatch between banking industry needs and current tertiary banking curricula. The purpose of the study to develop an industry-realistic CRIS prototype that embeds event-driven architecture, feature stores, explainable AI, and real-time predictive analytics into classroom practice so students acquire the technical, regulatory, and decision-making competencies required for modern credit risk management. This research uses a design-based research (DBR) approach guided iterative prototype development. A DBR-driven, event-aware CRIS simulation is an effective educational intervention to align banking education with the technical and governance demands of contemporary credit risk management.

Introduction

The global financial services industry is characterized by a pervasive and accelerating digital transformation (DT), which has profoundly impacted banking operations by improving efficiency and enhancing overall customer satisfaction (Srinija et al., 2025). Commercial banks are increasingly leveraging DT initiatives to anticipate rapidly evolving customer needs, allowing them to construct appropriate business models and streamline loan processes and this strategic modernization effort is positively associated with an increase in the revenue of commercial banks, largely achieved through the enrichment of loan products and significant efficiency gains (Podder & Ghosh, 2025).

The current financial landscape is full of complicated regulatory requirements and unstable market dynamics, which makes digital solutions necessary. Consequently, risk functions within financial institutions are now expected to deploy sophisticated machine learning (ML) models across critical operational areas, including credit underwriting, early-warning systems, and the detection of financial crime (Härle et al., 2015). For organizations looking to preserve operational resilience and regulatory compliance in this complicated and quickly changing financial sector, integrating AI-driven solutions is crucial.

The Talent Gap and the Educational Imperative

The primary characteristic of financial institutions is their function as risk managers, which includes evaluating creditworthiness, carefully controlling liquidity exposures, and negotiating complex regulatory environments. Despite substantial investment in managing traditional financial exposures, the banking industry faces a critical, often unmeasured, internal risk: the widening talent gap, where existing employee capabilities lag behind the pace of technological evolution, and this deficiency is exacerbated because rigid and routine work environments within banking often drive employee disengagement and turnover, causing many financial institutions to struggle significantly in attracting young talent (https://thefinancialbrand.com/news/bank-culture/the-silent-banking-risk-why-talent-gaps-can-be-as-dangerous-as-credit-gaps-188598).

This professional skills deficit highlights the persistent limitations of traditional educational models that frequently fail to provide the advanced analytical skills required to operate digital-first banking platforms (https://thefinancialbrand.com/news/bank-culture/the-silent-banking-risk-why-talent-gaps-can-be-as-dangerous-as-credit-gaps-188598). Furthermore, research demonstrates that a lack of adequate financial literacy among young adults is linked to more pronounced risk-taking behavior, emphasizing a broader societal need for sophisticated financial education (https://thefinancialbrand.com/news/bank-culture/the-silent-banking-risk-why-talent-gaps-can-be-as-dangerous-as-credit-gaps-188598). Regulators have suggested creating standardized, easily accessible instructional materials, such loan simulators, budgeting manuals, and financial rights handbooks, to help people accurately assess their risks in order to overcome these structural weaknesses. Effective financial education has also been demonstrated to assist people in reducing the emotional and cognitive biases that often affect personal credit decisions, resulting in the adoption of more responsible and informed financial decisions.

Predictive analytics' incorporation into credit risk management is a revolutionary development in the banking industry, fueled by the quick development of sophisticated analytical techniques and data processing technologies and this paradigm change is a reaction to the more complicated financial environment, which is marked by erratic market circumstances and the urgent need for more precise and effective risk assessment tools. It also reflects technology improvement (Addy et al., 2024). It is impossible to overestimate the importance of predictive analytics in this field since it helps financial institutions become more stable and profitable by improving their capacity to reduce possible losses related to credit risk (Lera et al., 2019).

In the past, banks utilized conventional risk assessment models that mostly concentrated on static variables like credit scores, income levels, and work histories, although these models have been useful, they are frequently criticized for failing to account for the dynamic character of financial markets and the intricate interactions of variables that impact the risk of credit (Addy et al., 2024). By introducing models that can analyze a wider range of variables, such as behavioral and transactional data, predictive analytics has addressed these limitations and provided a more complex and thorough picture of a borrower's creditworthiness (Bonini and Caivano, 2021).

The use of predictive analytics and machine learning in credit risk management has been shown to improve risk assessment accuracy through empirical validation (Addy et al., 2024). For example, it has been demonstrated that neural networks, a class of machine learning models, perform better than conventional models in forecasting the likelihood of default, allowing banks to make better loan decisions (Bonini and Caivano, 2021). The democratizing impact of these technologies in the financial industry is further demonstrated by the fact that the application of big data analytics has enabled credit unions and smaller financial institutions to use predictive insights for boosting profitability and competitive advantage (Millerman, 2023).

ISSN 2747-089X

Credit risk management has been further revolutionized by the emergence of big data and advancements in computer technologies, also large volumes of data, including non-traditional data sources like social media and transactional data, are now available to banks and can offer deeper insights into borrower behavior (Addy et al., 2024). Predictive models that can evaluate this data in real time and provide a more sophisticated and forward-looking evaluation of credit risk have been made possible by machine learning algorithms and artificial intelligence. Additionally, these technologies have made it easier to automate credit decision-making procedures, increasing their accuracy and efficiency (Yuan and Zhang, 2021).

An Overview of Predictive Analytics

A paradigm shifted in the way financial institutions handle risk management, customer service, and decision-making is represented by predictive analytics in banking, and this revolutionary technology analyzes current and past data to forecast future occurrences using a range of statistical, machine learning, and artificial intelligence methodologies (Addy et al., 2024). Predictive analytics is used in many aspects of the banking industry, such as product personalization, fraud detection, credit risk assessment, and customer relationship management (Andriosopoulos et al., 2019).

Predictive analytics' fundamental strength is its capacity to analyze enormous volumes of data in order to find patterns and trends that are not immediately obvious, and compared to previous approaches, which frequently rely on intuition or simple heuristics, this data-driven approach provides a more objective and quantifiable means for making decisions (Addy et al., 2024). Predictive analytics algorithms, for example, can evaluate a borrower's creditworthiness in credit risk management by examining their financial history, transaction patterns, and even social media activity. According to Shaheen and Elfakharany (2018), this thorough research aids banks in lowering default risk and enhancing the general quality of their loan portfolios.

Additionally, predictive analytics is essential for improving consumer engagement and experience, and predictive models are used by banks to evaluate consumer data and forecast their requirements and preferences (Addy et al., 2024). This increases client happiness and loyalty by allowing them to provide customized goods and services, for example, banks can provide customized credit card or loan solutions that meet each customer's unique needs by evaluating spending patterns (Andriosopoulos et al., 2019).

The Role of Predictive Analytics in Banking

Fraud detection heavily relies on predictive analytics and machine learning models are used by banks to spot trends and abnormalities that might point to fraud (Addy et al., 2024). These models are able to retain high levels of accuracy over time by learning from new kinds of fraudulent activity and modifying their algorithms accordingly. This is especially crucial in the digital era since financial fraud's characteristics and techniques are always changing (Andriosopoulos et al., 2019).

Improving customer experience and engagement is a key use of predictive analytics in banking and predictive models are used by banks to examine client data and forecast their requirements and preferences (Addy et al., 2024). This makes it possible for them to provide customized goods and services, increasing client loyalty and pleasure, for example, banks can provide customized credit card or loan solutions that meet the unique demands of individual clients by evaluating spending patterns (Korns & May, 2019). Furthermore, predictive analytics significantly affects banking's operational effectiveness and banks can cut down on the time and resources needed for jobs like credit scoring, risk assessment, and marketing campaign management by automating intricate analytical procedures (Addy et al., 2024). In addition to

 ISSN 2747-089X

increasing productivity, this automation lowers the possibility of human error, producing more precise and trustworthy results (Nwafor et al., 2019).

Methodologies and Technological Advancements in Predictive Analytics

Predictive analytics now have access to a wealth of information thanks to the emergence of big data and large datasets may now be processed and analyzed to find hidden patterns and insights when combined with machine learning algorithms (Addy et al., 2024). For example, radio frequency identification (RFID) technology and big data predictive analytics are being employed in the pharmaceutical business to improve supply chain performance (Mishra et al., 2019). Researchers can now examine complex genomic data more quickly and accurately thanks to high-performance computing. This advancement is demonstrated by the application of scalable naïve Bayes-based algorithms for genomic data analysis, which provide excellent sensitivity, specificity, and accuracy in predictive analytics (Leung, Sarumi & Zhang, 2020). Predictive maintenance has seen a revolution thanks to the Internet of Things (IoT) and IoT-driven predictive maintenance improves system longevity and encourages sustainable operations across a range of industries by utilizing advanced data analytics, artificial intelligence, and machine learning (Addy et al., 2024). This strategy improves system durability and operating efficiency by resulting in more precise and timely maintenance interventions (Gidiagba et al., 2024).

Study Objectives and Research Gap

The banking industry's transition from reliance on historical centralized data systems necessitates the ability to manage complex, real-time credit intelligence for next-generation risk management, and current academic curricula fail to replicate the complex AI-driven, event-based architectural demands now standard in financial risk departments (Sebastian, 2025). Bridging this divide requires the integration of authentic, work-focused experiences, formally known as Work-Integrated Learning (WIL), into the curriculum as an intentional component of professional development (McKenzie et al., 2025). WIL ensures that students learn through active engagement in purposeful work tasks that explicitly merge theoretical principles with meaningful practice relevant to their chosen discipline (https://www.portotheme.com/the-impact-of-real-world-scenarios-on-investment-banking-education). This study addresses the persistent gap between theoretical instruction and professional practice by proposing the design, architecture, and validation framework for a novel Data-Based Information System for Credit Risk Management (CRIS) which has not been implemented in previous studies (Smeltzer & McCracken, 2025; McKenzie et al., 2025; Spante et al., 2025).

Transitioning to AI-Driven Risk Assessment

The evolution of professional credit risk assessment demands a shift away from traditional linear statistical models, such as linear regression (LR), which are limited by linear assumptions and possess difficulty in identifying complex risk associations (Zhong, 2025). Modern credit risk modeling requires the incorporation of Artificial Intelligence (AI) and Machine Learning (ML) methods due to their proven ability to analyze large volumes of complex data and substantially improve out-of-sample default prediction (Noriega et al., 2023). Advanced algorithms, are particularly effective because they leverage the Gradient Boosting (GB) framework to capture the non-linear characteristics of default samples, yielding higher predictive accuracy compared to older linear models (Zhong, 2025). The increasing impact of big data characteristics, particularly the velocity and variety of information, necessitates the use of neural network algorithms, such as the backpropagation (BP) neural network, to mitigate information asymmetry and improve overall credit risk assessment accuracy (Wang & Perkins, 2025). Predictive analytics fundamentally relies on assessing past performance and integrates time series information combined with sophisticated regression and neural network capabilities, specifically, deep learning models, such including Long Short-Term Memory (LSTM) networks, are well suited to handling time-series data like transaction histories for predicting loan default risks and future portfolio performance (Karami & Igbokwe, 2025).

Method

We use design-based research framework for CRIS simulation development in this research. The development of the Data-Based Information System for Credit Risk Management (CRIS) prototype must follow a rigorous, iterative structure to ensure both technical fidelity to industry standards and demonstrable pedagogical efficacy (Momand et al. 2022). Design-Based Research (DBR) is selected as the primary methodology, given its proven suitability for simulation-based education, organized into four essential stages: design, testing, evaluation, and reflection (Momand et al. 2022). This framework strategically integrates architectural realism with instructor usability, balancing the system's function with its learning utility.

The first step of DBR is Problem Analysis and System Requirement Specification (SRS). The System Requirement Specification (SRS) for the educational CRIS prototype must align the simulation content with the forward-looking credit metrics required by industry regulators and key functional requirements defined in the SRS include the ability for student teams to analyze the distribution of simulated loan grades and track their migrations over time (https://www.fdic.gov/bank-examinations/credit-management-information-systems-forward-looking-approach). Furthermore, the system must facilitate the use of multi-source heterogeneous data, including behavioral, demographic, operational, and payment history data, mirroring the complex fusion of public and private datasets used in real-world credit applications (Noriega et al., 2023).

The second step of DBR is define prototype design and architecture. The architectural design of the CRIS prototype intentionally employs a modular, event-driven architecture (EDA) to accurately mimic the modern, robust, real-time financial risk systems utilized by multinational banks (Sebastian, 2025). This architectural choice is fundamentally pedagogical because the asynchronous processing of events enforces the principle of immediate consequence inherent in dynamic risk management (Tleubay, 2025). This necessity for instantaneous response compels students to practice proactive risk mitigation and continuous portfolio monitoring, exceeding the limitations of delayed, traditional grading systems.

Stage 3 and 4 of DBR are evaluation and reflection. The validation process necessitates a complex dual standard, simultaneously verifying the internal technical efficacy of the AI models and the external educational success in competency transfer (Halkiewicz & Stachowicz, 2025). This methodological requirement accounts for the dual necessity of proving both realism and learning utility.

Result

Key architectural components of the educational CRIS prototype presented in Table 1 below.

Table 1.1: Key Architectural Components of the Educational CRIS Prototype

Component Layer	Industry Function	Pedagogical Function in Simulation
Data Ingestion/Feature Store	Real-time intake of multi-source heterogeneous data; feature reuse for ML models	Providing complex, governed, and audited digital footprints for student credit assessmen
Risk Modeling Engine	Deployment and optimization of advanced models (NN, XGBoost, Gen AI) for default prediction	Allowing students to validate, compare, and parameterize complex credit scoring techniques against regulatory benchmarks
Event-Driven Alerting System (EDA)	Processing triggers from real-time credit data feeds for immediate risk response and portfolio adjustment	Enabling instantaneous feedback on lending decisions, simulating market volatility, and practicing proactive risk mitigation
Interpretability/Governance Modules	Implementation of tools and metadata tracking for auditability and compliance	Teaching students how to interpret "black box" decisions and ensuring decision logic is transparent for regulatory review

Source: Analysis of researchers (2025)

Discussion

The utilization of an Event-Driven Architecture (EDA) is crucial for this pedagogical success because it provides instantaneous feedback on lending decisions, mirroring the dynamic and proactive risk mitigation required in real-time banking environments (Tleubay, 2025). This immediate consequence and decision loop is vital for effectively mitigating financial risks in highly uncertain environments. The system is capable of exposing students to current, high-level systemic risks, such as those arising from the unregulated nature of Decentralized Finance (DeFi), Metaverse vulnerabilities, and the growing importance of ESG disclosure requirements, which are at the forefront of contemporary financial risk journals (Gautam & Singh, 2025). By mastering fundamental risk tracking (e.g., managing loan grade migrations and portfolio concentrations) within the system, students develop the analytical framework necessary to apply risk assessment principles to emerging macro-level challenges, proving the simulation's future-proof value (Wu & Yang, 2025).

The deployment of the high-fidelity CRIS simulation is anticipated to yield substantial improvements in student learning retention and pattern recognition skills. By actively tackling portfolio management challenges under realistic, simulated market pressure, students learn firsthand how to handle stringent regulatory requirements and dynamically optimize portfolio performance. The utilization of an Event-Driven Architecture (EDA) is crucial for this pedagogical success because it provides instantaneous feedback on lending decisions, mirroring the dynamic and proactive risk mitigation required in real-time banking environments. This immediate consequence and decision loop is vital for effectively mitigating financial risks in highly uncertain environments. The system is capable of exposing students to current, high-level systemic risks, such

ISSN 2747-089X

as those arising from the unregulated nature of Decentralized Finance (DeFi), Metaverse vulnerabilities, and the growing importance of ESG disclosure requirements. By mastering fundamental risk tracking (e.g., managing loan grade migrations and portfolio concentrations) within the system, students develop the analytical framework necessary to apply risk assessment principles to emerging macro-level challenges, proving the simulation's future-proof value

The successful integration of the complex CRIS system relies on overcoming the educational challenge of seamlessly integrating technology with pedagogy, as outlined by the TPACK framework. The application of the DBR approach ensures that the system design aligns the simulation (Technology) directly with the teaching of sophisticated credit risk concepts (Content) through experiential learning (Pedagogy). The system addresses the crucial industry requirement for transparency by providing instructors with interpretable XAI tools. This pedagogical use of XAI allows faculty to demonstrate how AI decisions are generated, effectively transforming a technical compliance issue into a powerful teaching moment about regulatory transparency and ethical modeling, moving beyond the functional limitations of "black box" models. Critically, the controlled environment of the simulation provides the platform necessary to observe and correct the cognitive and emotional biases that influence credit decisions, translating behavioral finance theory into tangible mitigation techniques. By incorporating tools like loan simulators and budgeting guides, the system not only facilitates advanced technical risk assessment but also promotes financial empowerment, aligning academic training with the broader Environmental, Social, and Governance (ESG) responsibilities expected of financial institutions.

The deployment of an AI-driven, data-based CRIS simulation represents a direct and essential solution to the critical talent gap identified across the banking sector. This specialized training prepares graduates with the necessary strategic and technical skills required to operate digital-first banking platforms. Evidence from similar simulation programs indicates that participants are significantly more likely to secure competitive positions in top financial institutions, demonstrating the translation of classroom learning into high vocational preparedness. Furthermore, the simulation provides a vital testbed where students can ethically experiment with innovative, complex models—such as Gen AI frameworks—before they achieve full industry or regulatory approval.

Conclusion

The accelerating digital transformation of the financial sector has exposed a critical talent gap, making the modernization of banking education curriculum mandatory. This report established the necessity and detailed the rigorous architectural and pedagogical framework for a Data-Based Information System for Credit Risk Management (CRIS), implemented as a high-fidelity educational simulation. The system development successfully utilized the iterative structure of Design-Based Research (DBR), ensuring the prototype meets stringent technical requirements while maximizing pedagogical effectiveness through the TPACK framework.

The CRIS prototype achieves technical realism by incorporating advanced architectural components, including Data Mesh design patterns, Feature Stores, and an Event-Driven Architecture (EDA) that provides instantaneous, real-time feedback on student risk decisions. The simulation engine supports sophisticated Machine Learning models, requiring students to master complex quantitative metrics like AUC and the F1 Score for model validation. Crucially, the system integrates Explainable AI (XAI) outputs, enabling instructors to teach the critical importance of compliance and transparency, thereby overcoming the operational limitations associated with "black box" models in regulated environments.

 ISSN 2747-089X

The proposed data-based CRIS simulation serves as a vital transformative tool that aligns academic instruction with the complex, risk-prone supra-systems of the contemporary financial industry. This experiential platform prepares future banking professionals to manage real-time credit intelligence, mitigate behavioral biases, and comply with advanced regulations, thereby directly addressing the critical skills deficiency in the digital banking era. The system promises to enhance analytical capabilities and strategic decision-making, offering a robust solution to the talent challenge facing global financial institutions.

This exposure fosters innovation and critical analysis in future professionals, teaching them the nuances of model validation and interpretability. Future research should focus on the socio-technical challenges inherent in digital learning ecosystems, specifically investigating issues of access, digital equity, and inclusivity, given the potential for digital tools to amplify inequalities. Additional controlled studies are required to rigorously assess the long-term retention, scalability, and adaptability of the CRIS prototype across diverse educational contexts.

References

Addy, W.A., Ugochukwu, C.E., Oyewole, A.T., Ofodile, O.C., Adeoye, O.B., & Okoye, C.C. (2024). Predictive analytics in credit risk management for banks: A comprehensive review. *GSC Advanced Research and Reviews*, 18(02), 434–449.

Andriosopoulos, D., Doumpos, M., Pardalos, P. M., & Zopounidis, C. (2019). Computational approaches and data analytics in financial services: A literature review. *Journal of the Operational Research Society*, 70(10), 1581-1599.

Bonini, S., & Caivano, G. (2021). Artificial Intelligence: The Application of Machine Learning and Predictive Analytics in Credit Risk. *Risk Management Magazine*, 16(1).

Gautam, D., & Singh, P. (2025). Metaverse momentum: analyzing financial system risks in an expanding virtual landscape. *Journal of Credit Risk*, 21(2). https://doi.org/10.21314/JCR.2025.008

Gidiagba, J.O., Nwaobia, N.K., Biu, P.W., Ezeigweneme, C.A. & Umoh, A.A. (2024). Review on the evolution and impact of IOT-driven predictive maintenance: assessing advancements, their role in enhancing system longevity, and sustainable operations in both mechanical and electrical realms. *Computer Science & IT Research Journal*, 5(1), 166-189.

Halkiewicz, S., & Stachowicz, M. (2025). An aggregated metrics framework for multicriteria model validation using rolling origin evaluation. *Journal of Risk Model Validation*, 19(3). https://doi.org/10.21314/JRMV.2025.013

Härle, P., Havas, A., Kremer, A., Rona, D., & Samandari, H. (2015). The future of bank risk management. *McKinsey Working Papers on Risk*, 1-31.

Karami, A., & Igbokwe, C. (2025). The impact of big data characteristics on credit risk assessment. *International Journal of Data Science and Analytics*, 20, 4239-4259. 10.1007/s41060-025-00753-8

Korns, M. F. and May, T. (2019). Strong typing, swarm enhancement, and deep learning feature selection in the pursuit of symbolic regression-classification. *Genetic and Evolutionary Computation*, 59-84. https://doi.org/10.1007/978-3-030-04735-1_4

Lera, I., Guerrero, C., & Juiz, C. (2019). YAFS: A simulator for IoT scenarios in fog computing. *IEEE Access*, 7, 91745-91758.

Leung, C. K., Sarumi, O. A., & Zhang, C. Y. (2020). Predictive analytics on genomic data with high-performance computing. *2020 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*. https://doi.org/10.1109/bibm49941.2020.9312982

McKenzie, S., Bangay, S., & Young, K. (2025). A case study analysis of the criteria used for authentic evaluation of information technology students' progress on workplace-based work-integrated learning. *International Journal of Work-Integrated Learning*, 26(3), 459-476.

Millerman, J.A. (2023). Credit unions and data analytics: How sophisticated analytics can drive profitability for local credit unions. *Business & IT*, 13(1), 68-73.

https://doi.org/10.14311/bit.2023.01.08.

Mishra, D., Luo, Z., Hazen, B. T., Hassini, E., & Foropon, C. (2019). Organizational capabilities that enable big data and predictive analytics diffusion and organizational performance. *Management Decision*, 57(8), 1734-1755. https://doi.org/10.1108/md-03-2018-0324

Momand, B., Hamidi, M., Sacuevo, O., & Dubrowski, A. (2022). The Application of a Design-Based Research Framework for Simulation-Based Education. *Cureus*. https://doi.org/14. 10.7759/cureus.31804.

Noriega, J. P., Rivera, L. A., & Herrera, J. A. (2023). Machine Learning for Credit Risk Prediction: A Systematic Literature Review. *Data*, 8(11), 169. https://doi.org/10.3390/data8110169

Nwafor, C. N., Nwafor, O. Z., & Onalo, C. (2019). The use of business intelligence and predictive analytics in detecting and managing occupational fraud in Nigerian banks. *Journal of Operational Risk*, 14(3), 95 -120. http://doi.org/10.21314/JOP.2019.227

Podder, B., & Ghosh, J. (2025). Digital transformation: how it impacts bank performance for emerging economies. *International Journal of Emerging Markets*, 1-21. https://doi.org/10.1108/IJOEM-05-2025-1108

Sebastian, D. (2025). Modernizing Credit Risk with Data Mesh: A Large Bank's Transformation to Real-Time Credit Intelligence. *Journal of Computer Science and Technology Studies,* 7(10), 650-664.

Shaheen, S.K. & Elfakharany, E. (2018). Predictive analytics for loan default in banking sector using machine learning techniques. *In 2018 28th International Conference on Computer Theory and Applications (ICCTA)*, 66-71. https://doi.org/10.1109/ICCTA45985.2018.9499147

Smeltzer, S., & McCracken, M. (2025). When theory meets practice: An embodied approach to supporting work-integrated learning students' wellbeing. *International Journal of Work-Integrated Learning*, 26(1), 129-141.

Spante, M., Garraway, J., Winberg, C., Nofemela, F., & Duma, T.P. (2025). A toolkit to enhance work-integrated learning coordinators' understanding of practical problems. *International Journal of Work-Integrated Learning*, 26(3), 477-491.

Srinija, K., Vaishnavi, K., & Ramana, S.V. (2025). A study on the impact of the digital transformation on banking sector with refernece to customer perspective. *International Journal of Research Publication and Reviews*, 6(3), 895-898.

Tleubay, A. (2025). Information Technology Approaches to Credit Monitoring Systems in Banking: Architecture, Implementation, and Use Cases. *Int. J. Sci. R. Tech*., 2(6), 335-341. https://doi.org/10.5281/zenodo.15615340

Wang, J.C., & Perkins, C.B. (2025). How magic a bullet is machine learning for credit analysis? An exploration with fintech lending data. Journal of Credit Risk. 21(1). https://doi.org/10.21314/JCR.2025.005

Wu, M., & Yang, Y. (2025). Hierarchical allocation method for capital: a general method. *Journal of Credit Risk*, 21(2). https://doi.org/10.21314/JCR.2025.015

Yuan, X., & Zhang, Y. (2021). Analysis of Bank Loan Risk Management Based on BP Neural Network. In *2021 4th International Conference on Information Systems and Computer Aided Education*. 2457-2461. https://doi.org/10.1145/3482632.3487450

Zhong, Y. (2025). A Comparative Study of Credit Scoring Machine Learning Models Based on Financial Indicators. *Proceedings of the 2025 3rd International Conference on Image, Algorithms, and Artificial Intelligence (ICIAAI 2025)*, 245-253. https://doi.org/10.2991/978-94-6463-823-3_23.