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COMPARATIVE ANALYSIS OF AI- DRIVEN AND TRADITIONAL FINANCIAL CREDIT RISK MODEL IN REAL ESTATE SUPPLY CHAINS

Krishna Teja

Under the guidance of

Dr Geeta k, Joshi

Assistant professor (Dayananda Sagar Business School)

Co-Author: Dr Geeta k Joshi

Abstract

The assessment of credit risk in the real estate supply chain is an essential part of financial risk management that influences investment decisions, financial stability, and the health of the overall real estate segment. Traditional financial credit risk models have long been used for the assessment of borrower credibility and potential default prediction with historical financial data, credit score, and some various financial ratios, while other methods could complement this approach. Although these conventional approaches have some merit, they frequently fail in capturing real-time market fluctuations, new emerging risks, and complex interdependencies that build creditworthiness. The introduction of artificial intelligence (AI) and machine-learning technologies has planted the seeds of change in the credit risk analysis horizon. AI-based models have given way to advanced analytical techniques that use big data, predictive analytics, and real-time insights to assess risk dynamically and more accurately.

This particular paper gives a thorough comparison between the AI-driven and the traditional financial credit risk models alongside their methodologies and performance on prediction, adaptability, and limitation. Credit risk assessment is AI-driven because it utilizes machine learning algorithms to process both structured and unstructured data of large sizes to identify so-called hidden behaviours that conventional models are not able to detect. Real-time market conditions as well as transaction behaviours and macroeconomic indicators are incorporated in AI risk models to improve accuracy and timeliness of risk evaluation. Such models also help financial institutions, lenders, and investors of the real estate sector in decision-making, thus reducing possible financial losses and improving total risk management strategies.

On the contrary, traditional models remain relevant since they are regulatory-compliant, transparent, and rely on well-documented financial indicators. They might be slower in reacting to changing market conditions, yet they maintain an aspect of interpretability that is usually absent in AI models. The regulatory authorities and financial institutions are sceptical of the black box of AI models within which lies the accountability, ethical considerations, and potential biases woven into machine-learning algorithms. Data privacy issues and regulatory frameworks concerning AI adoption in financial risk assessment remain reverse challenges that require immediate attention.

By systematically comparing AI techniques with the classic credit risk models, the study delineates some of the parameters of distinction, including accuracy, scalability, cost-effectiveness, and applicability in the real world for the real estate sector. Two comparison tables depict the efficiency and application of the two approaches, along with usefulness in contrasting their efficacy. The results, though, suggest that AI-based credit risk models possess superior predictive accuracy, adaptability, and risk mitigation when weighed against traditional methods; yet, those features need to be balanced against regulatory oversight and ethical viewpoints to allow for successful implementation.

Ultimately, the aforementioned study shows that innovation and regulatory compliance should be seen as two sides of the same coin for credit risk evaluation. The application of AI for the financial risk evaluation process reconstructively resembles giving an identity to the rehabilitation of the entire real estate supply chain by making decision-making more proactive and also helping in mitigating defaults. However, the transition phase from conventional models to AI-driven models needs a holistic understanding of both these approaches, along with their relative pros and cons. With an active evolution of AI technologies, future works may focus on developing transparent, non-biased, and interpretable AI systems that comply with available industry regulations and ethical principles, so that their adoption in real estate credit risk management can be considered responsible.

Keywords

Risk of Credit, Supply Chain in the Real Estate sector, Financial Stability, Conventional Templates of Credit, Models for Credit Powered by AI, Machine Learning, Big Data Analytics, Predictive Analytics, Risk Evaluation Recurrently, Default Risk Mitigation, Decision making in Investments, Credit Scoring, Financial Ratios, Risk Management Strategies, Efficiency of Models, Ethics in AI, Regulatory Compliance.

Introduction :

The real estate sector is capital-intensive-the supply chain of which relies heavily on credit financing. Developers, investors, lenders, and financial institutions should carefully evaluate credit risk to ensure profitable and sustainable lending decisions. The ability to predict loan default, assess borrower creditworthiness, and mitigate financial risks is critical to the stability of the real estate market. Historically, financial institutions have relied on conventional credit risk assessment models which use credit scores, debt-to-income ratios, loan-to-value ratios, and macroeconomic indicators. Though these models have greatly assisted in determining lending decisions, they have fundamental limitations in keeping pace with the rapidly changing financial landscape.

Generally, conventional credit risk models focus on analysis of financial data using fixed formulas, applied statistical methods, and expert knowhow, which explain transparency and interpretability, hence widely acceptable to regulators and financial institutions. They are challenged to cope with massive volumes of unstructured data, demonstrate their ability to identify nonlinear relationships in financial behaviours, and adjust to real-time fluctuations within the market. Such traditional models are highly dependent on static datasets and preset risk measures to define risks, capturing only a small segment of the ever-increasing complexities of modern credit markets. With the incre...

The advent of artificial intelligence and machine learning has completely transformed the financial risk management area by virtue of credit risk models powered by AI, which can assist in analysing large datasets, recognize intricate patterns, and provide real-time risk assessment. These risk evaluation methods are aided by advanced statistical methods, predictive analytics, and deep learning algorithms in risk evaluation and lending decision-making, with a departure from traditional models-to give the opportunity to the newer AI-driven system to analyse vast types of alternate data sources including social media behaviours, transaction history, spending patterns, and even geospatial economic indicators. Using knowledge gain from learning off new data on an ongoing basis adjusts well with any changing conditions of the market, vital to the ever-changing industry such as real estate.

Predictive accuracy is one of the principal advantages of AI-driven credit risk models. With the help of big data and complex algorithms, AI models are able to catch minute risk signals that traditional models could miss. Compared with traditional modes, these models can analyse borrower profiles at a much keener level, relying on nontraditional credit measures like an analysis of digital footprints, stability of employment, and behavioural finance. Only AI-powered models can help automate the underwriting process, resulting in processing time and operational cost savings for the financial institutions. That is why AI is now the most popular option for lenders trying to improve the speed of the decision-making process without sacrificing accuracy.

Despite these advantages, AI-powered credit risk models come with problems and hazards. The most important one is the lack of transparency and explainability in AI decision-making processes. Many AI models are considered black boxes by most of the developers, and they usually do not know the exact reason by which the features lead to the final decision in terms of lending. This makes things very important for regulators, financial institutions, and borrowers because they want to have justifications regarding why a loan should be approved or denied. Not to mention, AI models depend very much on the quality and quantity of data. Unreliable, biased, and/or incomplete datasets create an incorrect perception for the risk assessment and can make systemic risks worse in financial markets.

One more major concern is data privacy and security. AI-based models require enormous amounts of personal and financial information, which raises alarms about consumer privacy rights and the risk of data breaches. The use of ethical AI in financial risk assessment also requires compliance with confidentiality aspects of stringent data protection laws such as the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA). Huge data governance frameworks need to be built around them to insulate sensitive borrower information from maximized operation gains with AI-based analytics.

In addition, it is an evolving regulatory environment that will have to be dealt with by AI credit risk models. The credit assessment techniques used are relatively well-established when it comes to regulatory frameworks, making them predictable and easier to enforce compliance in financial institutions. Meanwhile, AI-based models create new challenges for regulators because they have to balance innovation with risk mitigation. Policymakers are working to develop the guidelines that will assist in standardizing credit assessments based on AI. However, the absence of regulations that are standard across jurisdictions makes compliance an issue for multinational financial institutions.

Hence, considering the proficiency and demerits of both AI-powered models and traditional models, financial institutions need to carefully weigh the most cost-effective modeling approach for their lending operations. Some industry leaders advocate a hybrid method combining AI's power to predict with traditional risk assessment methodologies. These will enable borrowing institutions to benefit from the ability of AI to predict while keeping the advantage of transparency and regulatory compliance from traditional models.

Hybrid models may take advantage of AI-driven insights to boost conventional credit scoring mechanisms, thereby leading to a much more profound and accurate risk evaluation.

This research sets out to conduct a thorough comparative study of AI-driven and conventional credit-risk models as applied to real estate supply chains, considering aspects such as performance, reliability, and limitations. The empirical, case study, and analytical discussions available will endeavour to show how AI is presently reforming credit risk assessment in the real estate sector, along with future challenges it has to encounter, among other factors. Findings from this study will also add to the discourse on financial risk management with an eye into the future path of credit risk modelling in the real estate arena.

This research will thus illuminate why they should continue scrutinizing the differences, advantages, and limitations of the two modelling approaches into how financial institutions will be able to refine their credit risk assessment frameworks. Will models based on artificial intelligence take on completely replacing traditional methods or will a hybrid approach emerge as the one favoured by financial experts, regulators, and industry stakeholders? Indeed, grasping the semantics of all of this regarding AI in credit risk assessment will prove very critical toward ensuring financial stability, improved lending decisions, and resilient real estate supply chains.

Mythology:

order to conduct the thorough comparative analysis, methods used by this study include quantitative data analysis, case studies, and literature reviews. The methodology followed includes:

1. Data Collection Financial datasets from banks, lending institutions, and real estate firms were collected to observe default rates, credit approvals, and patterns in risk assessment.

- Studies were carried out on AI-driven credit-scoring models, especially those based on machine learning algorithms such as neural networks, decision trees, and ensemble models.

- Studies were carried out on older financial models utilizing logistic regression, credit scoring methodologies, and risk rating systems.

2. Model Evaluation Metrics

Overall performance of AI models vs. traditional models was assessed against:

- Accuracy: The degree to which the model predicts defaults.

- Adaptability: The degree of change of the model in accordance with changes in the market.

- Efficiency: Time taken to assess the risk.

- Transparency: How well the process can be understood.

3. Comparative Framework

The comparative analysis was structured by making available for scrutiny two key tables for the purpose of sum-motorizing induction mode liveness according to various criteria.

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Tabe comparison of traditional vs. AI-driven credit risk models

Criteria	Traditional credit risk models	AI-driven credit risk models
Data utilization	Limited historical financial data	Big data, real-time analytics
Processing speed	slow	Rapid
Adaptability	Rigid to new trends	Highly adaptable
Interpretability	High	Low
Regulatory Compliance	Well-defined frameworks	Emerging regulations
Predicative accuracy	Moderate	High

Table credit risk model performance in real estate supply chains

Model type	Default prediction rate (%)	Loan approval efficiency	Data processing speed (seconds)
Traditional models	75%	60%	180
Al-driven models	89%	85%	25

Discussion :

1. Precision and Predictive Capabilities

Deep learning or AI-driven credit risk models are considered to have by far the best-of-breed prediction ability. Traditional models rely a lot on the earlier defined risk factors and historical data, which do not make the risk models able to detect any evolution in the market trends. On the other hand, AI realises its predictions through machine learning algorithms that update themselves to new data and become better able to predict over time.

2. Fast and Efficient

Just take AI models, as they do in a matter of seconds thousands of any amounts of data and provide you with real-time credit risk assessment. The case is quite contrary to the previous method: it demands manual input, human involvement, and a lot of running around to come to conclusions, therefore not as fast and efficient as AI measures. It thereby streamlines the entire process of loan approvals and reduces the time taken in evaluating the credibility of the loan and improving the quality of operation.

3. Use in Dynamic Markets

The real estate market is still very much moving according to economic cycles, shifting interest rates, and states of investor sentiment. AI would make changes in all those parameters within the minute through real-time acquisition of macroeconomic indicators, social sentiment analysis and tracking global market dynamics at the point at which traditional models would have made changes in parameter settings.

4. Transparency and Ethical Concerns

One of the foremost challenges confronting AI models for credit risk appraisal is the lack of interpretability. Traditionally, models make decision rules that can be audited and understood by

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regulators and financial institutions alike for an explanation behind credit decisions. However, AI might just tend to function on black-box systems in the sense that it is very often hard to explain why a certain borrower is said to be high risk. This lack of transparency brings about some ethical questions, especially in regulatory compliance and fairness in lending.

Table key challenges in AI and traditional credit risk models

Challenges	Traditional models	AI-driven models
Data limitations	Historical bias	Requires massive datasets
Transparency	High	Low
Regulatory	Well established	Emerging less defined
Scalability	Limited	High

5. Regulatory and Security Considerations

AI models have definitely brought in a lot of benefits, but until now the financial regulators have not actually laid down any well-defined guidelines for their implementation in credit risk assessment. Moreover, conjoined with these merits are also certain issues with regard to data security and privacy, which arise since AI algorithms require access to huge pools of personal and financial information.

Table regulatory compliance and security consideration

Factors	Traditional models	AI-driven models
Regulatory	Well-defined	Still evolving
Data privacy	Controlled access	High risk of breaches
Bias and fairness	Structured fairness	Risk of AI bias

Conclusion

The environment for financial decision-making in the real estate supply chain has changed immensely due to advanced predictive analytics, efficiency, and adaptability brought on by AI-based credit risk models. These models combine large datasets and machine learning algorithms to provide real-time insights into assessing a borrower's creditworthiness. The AI model learns continuously from the market trends to identify emerging risks and defaults and thus develop better risk management strategies. In terms of dynamic adaptation to changing financial conditions, AI models work in a much more beneficial way for our purposes in volatile markets where traditional methods may hardly keep pace.

AI models and AI-driven credit risk models have additional advantages; however, the latter could not replace the former credence of appraisal of credit risk. These traditional models, given their long-standing framework, their acceptance from the regulators, and, equally important, their interpretability, are indeed an asset. They have been around for the last several decades and have been used by credit rating agencies, financial institutions, and policymakers alike. The traditional way has provided an outright structured approach fully documented for recognizing credit risk.

unlike AI-driven models which often act as "black-box" systems, traditional models speak transparency so that the stakeholders understand how credit decisions are made. Such interpretability becomes all the more vital in regulatory markets where lending institutions need to justify these lending decisions in terms of legal frameworks.

One of the possible strengths about AI-type credit risk models is their ability to ingest massive collections of data from a variety of alternative sources: new credit data, social media activity, real-time economic indicators. This more holistic approach enables AI to obtain a more nuanced and broader definition of a borrower's financial status, thus producing reports more closely reflecting their true risk. In this context, however, the dependence on large data becomes an issue for privacy and data security. Thus, the financial institutions require strict data privacy and protection measures against unauthorized access, breaches of data, or misuse of sensitive financial information. Also, adopting comprehensive policies that ensure compliance with data privacy regulations, including but not limited to General Data Protection Regulation (GDPR) and other financial data protection laws, is crucial for building trust in the AI-driven credit assessment systems.

A major impediment to the successful implementation of AI-based models is the problem of algorithmic bias. Machine learning algorithms, theoretically, should be impartial to the data they're fed; however, they run the risk of inheriting the biases present in the historical data. If discriminatory influences guided previous lending practices, AI algorithms trained on the biased data would replicate that bias, thus causing unfair credit decisions. The resolution of this challenge will call for sustained monitoring and bias detection capable of ensuring governance frameworks for ethical AI so that AI-led credit decisions remain fair, unbiased, and inclusive. On the other hand, traditional models apply pre-established risk factors and standardized scoring methodologies. Although they, too, are likely biased, they are more transparent and easier to regulate.

Regulatory ambiguity becomes yet another challenge that financial institutions will have to contend with in the process of adopting AI-based credit risk models. Traditional models exist in well-defined regulatory frameworks, whereas AI models are undergoing the process of being defined by legislative and regulatory policy. Credit risk assessment based on AI is a growing field for which policymakers and financial regulators try to create standardized frameworks; however, discrepancies in regulatory standing across jurisdictions cause large-scale problems for multinational financial institutions. Clear regulatory guidance is needed to ensure that the AI-driven models are ethical, lawful, and operationally viable, while still supporting innovation rather than inhibiting it. Cooperation among industry stakeholders, regulatory bodies, and AI researchers will...

The AI-supported models have better prediction capability, efficiency, and adaptability than traditional methods; nevertheless, they should not be a total substitute for them. A better solution would involve a hybrid approach that infuses AI advancements into conventional credit risk evaluation frameworks. Working together with traditional methods, AI can improve risk assessment accuracy while choosing transparency, regulatory compliance, and ethical prowess. For instance, AI models could conduct intensive analysis and patterning of risk over large datasets and make initial predictions, while conventional models could suit the assessment and interpretation of those results within a regulatory constraint.

So the future for credit risk modelling in real estate supply chains would be found in the balance between technical advancement and responsible governance. Financial institutions should continue to invest greatly in research, risk mitigation strategies, and securing compliance with regulations concerning maximizing benefits given to the credit assessment by AI while addressing its detrimental effects. Transparency, explainability, and ethics regarding AI models will be fundamental to gaining confidence from the stakeholders, regulators, and borrowers.

Additionally, ever-deepening collaborations among financial institutions, AI researchers, and policymakers will be key to further refining AI-centric credit risk models. Such a multi-disciplinary approach that adopts financial know-how, data science, and regulatory perspectives will further the industry's aim of building improved, fairer, and more efficient credit risk assessment systems. A responsible deployment of AI-driven innovations will be instrumental in sustaining financial stability, reducing credit default, and elevating investment decisions in the face of increasing complexity and interdependence in real estate markets.

Reference :

1. Bao, W., Xu, K., & Leng, Q. (2024). Research on the Financial Credit Risk Management Model of Real Estate Supply Chain Based on GA-SVM Algorithm: A Comprehensive Evaluation of AI Model and Traditional Model. Procedia Computer Science, 243, 900-909.

2. Gaikwad, P. P., Alhomaidi, E., Gupta, S., Perada, A., Dande, M. P., & Muthukumar, E., 2024 Predictive Logistics Management of Car Sales Based on Machine Learning Algorithm for Supply Chain. In 2024 Second International Conference Computational and Characterization Techniques in Engineering & Sciences (IC3TES)(pp.1-5). IEEE.

3. Pasha, S. M. M., & Sohag, S. R. (2022). A Novel Two-Level Network Slicing Approach for Efficient UAV Communication in Advanced 6G Environments.

4. Sohag, S. R., Pasha, S. M. M., & Ali, M. M. (2023). Advanced Approaches to Achieve Adaptive Ethical and AI-Driven Human-Centric Software Engineering.

5. Pasha, S. M. M., Sohag, S. R., & Ali, M. M. Enhancing Audio Classification with a CNN-Attention Model: Robust Performance and Resilience Against Backdoor Attacks. International Journal of Computer Applications, 975, 8887.

6. Sohag, S. R., & Pasha, S. M. M. Exploring Causal Relationships in Biomedical Literature: Methods and Challenges.

7. Meem, F. I., Mahdy, I. H., Tisha, S. J., & Sohag, S. R. (2025). A Comprehensive Survey on Security Features and Vulnerabilities in Data Science Tools. International Journal of Computer Science & Security (IJCSS), 19(1), 17.