THE INFLUENCE OF MACHINE LEARNING ALGORITHMS ON CREDIT SCORING STRATEGY IN FINTECH: A PROPOSAL FOR COMPARATIVE RESEARCH

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Abstract

Financial technology (FinTech) and data analytics raise the bar on the level of accuracy, inclusiveness, and effective risk management compared to conventional models. Markov et al. (2022) and Quach et al. (2022) present a comparative study related to data analytics and machine learning algorithms of credit score modelling between traditional financial institutions and FinTech startups. The paper discusses the consequences of such models for financial inclusion and risk management. This research, based on a mixed-method approach that combines quantitative analysis of credit scoring model performance with qualitative insights from interviews with industry experts, demonstrates the key differences in effectiveness and efficiency between the two sectors. Whereas traditional banks often rely on historical financial data, FinTech companies use alternative data sources supplemented by advanced analytics, promising speedier and more inclusive credit decisions. Furthermore, the paper develops implications for financial inclusions and risk management, which imply that FinTech credit scoring might act as a conduit to reaching out with credit to the relatively unserved parts of the population, while engendering challenges like algorithmic bias and regulatory oversight. This paper develops a very elaborate view of the current financial landscape and hence underlining practical and theoretical insights into the study, while giving some recommendations to traditional financial institutions, policymakers, and even the FinTech firms themselves.

Keywords: Financial Technology, Data Analytics, Machine Learning, Credit Scoring, Insights

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1. INTRODUCTION

The rapid growth of financial technology (FinTech) firms over the past years has completely changed the scenarios in the financial industry. Shifting consumer preferences and advances in technology have catalyzed its growth and depicted an environment of dynamic innovation. Certain broad ranges of financial services included under the category known as FinTech are digital payment systems, peer-to-peer lending platforms, blockchain-based cryptocurrencies, and robo-advisors. These services offer innovative ways to manage money and draw credit, both on an individual and corporate level. Indeed, these are innovations that call for a sensible understanding of their consequences on the financial system because they come with potential benefits and unique challenges at the same time. It is, therefore, imperative that research be diligently carried out to assess the impact of FinTech on various dimensions of finance, such as credit scoring, risk management, and financial inclusions.

The impact of FinTech on a nation's economy is diverse, providing prospects for expansion, employment generation, and enhanced financial access (Ebirim & Odonkor, 2024). FinTech promotes economic growth by cultivating innovation and enhancing efficiency in the financial industry, which in turn encourages entrepreneurial activity and generates employment opportunities in diverse sectors (Alyaqoot et al., 2022; Xie & Huang, 2024). Furthermore, the focus of FinTech on empowering users and reducing costs provides advantages to both consumers and businesses. This results in improved financial accessibility, consumer trust, and efficiency. However, to achieve these advantages, it is necessary to tackle obstacles such as cybersecurity risks, adherence to regulations, and market disturbances to guarantee the stability and durability of the financial system (Kamuangu, 2024).

FinTech's influence on the public varies and is contingent upon factors such as regulatory frameworks, technological infrastructure, and societal needs, despite its potential for transformation (Harsono & Suprapti, 2024). FinTech can enhance the capabilities of individuals and small businesses by granting them access to banking, lending, and investment services. This, in turn, can foster financial inclusion and encourage economic participation. Furthermore, the emphasis of FinTech on transparency, choice, and user experience improves consumer empowerment, financial literacy, and satisfaction (Xu et al., 2024). Nevertheless, it is crucial to address and reduce risks such as concerns regarding the privacy of data, biases in algorithms, and fluctuations in the market to protect consumer rights and guarantee fair and equal access to the advantages of FinTech innovation (Quach et al., 2022).

Several academic articles offer valuable insights into the profound impact of FinTech on the financial sector. Murinde et al. (2022) conducted an extensive study on the adoption and effects of FinTech in the banking sector. They emphasized the significance of technological innovation in transforming conventional banking methods and enhancing customer experiences. In their study, Xie et al. (2023) examined the consequences of blockchain technology on financial services, with a particular focus on its ability to improve transparency, security, and efficiency in transactions. In addition, Al-Afeef et al. (2024) conducted a study on the impact of peer-to-peer lending platforms on enhancing financial inclusion. They demonstrated how these platforms effectively enable underserved populations to obtain credit. Shi et al. (2022) examined the literature on difficulties and possibilities linked to the implementation of machine learning algorithms in credit scoring. Their research provided insights into the potential advantages and hazards of utilizing advanced analytics in lending practices.

These academic publications emphasize the significant and far-reaching influence of FinTech on the financial industry, highlighting the necessity for ongoing research to gain a comprehensive understanding of its consequences. Through the deployment of empirical evidence and theoretical frameworks, these studies offer valuable insights into the changing field of finance and establish a basis for future research works. Hence, given the ongoing transformation of the financial industry by FinTech, it is crucial to engage in interdisciplinary research endeavors to thoroughly evaluate its impacts and devise approaches to optimize its advantages while minimizing potential hazards.

This study focuses on examining how FinTech adoption influences credit risk assessment and lending decisions, considering the very critical determination of quality and effectiveness of FinTech credit-scoring models for how effective they are ultimately in promoting financial inclusion and risk management. It specifically tests such models for efficiency compared to those in traditional methods by incorporating data analytics and machine learning algorithms. It assumes that the introduction of non-traditional data sources would boost accuracy and efficiency. The hypotheses are as below:

H1: FinTech credit-scoring models have greater predictive accuracy in assessing credit risk as opposed to that of traditional models.

H2: FinTech credit scoring models improve access to credit by non-served and underserved populations, hence further improving financial inclusion.

H3: Machine learning algorithms in FinTech reduce bias and increase efficiency in making credit assessments.

It identifies the greater consequences of credit scoring through FinTech, since they bring new opportunities to extend credit access for under-represented consumers and public, yet also cover risks associated with algorithmic bias and higher default rates with a view to fostering critical discussion of ethical issues arising and related regulation in this evolving domain.

This research is significant in the financial industry as it provides valuable insights that can be used to make informed strategic decisions and develop regulatory frameworks. Through the assessment of the efficacy of FinTech credit scoring models, it offers valuable direction for financial institutions and FinTech companies, enabling the enhancement of credit evaluation procedures and potentially decreasing default rates. Moreover, the examination of FinTech's contribution to advancing financial inclusion highlights the necessity of implementing supportive policies and regulatory frameworks to guarantee fair and equal access to credit. Furthermore, conducting an examination of correlated hazards acts as a proactive approach to tackle possible prejudices and difficulties, fostering conscientious artificial intelligence (AI) methodologies in the FinTech industry and contributing to its ongoing growth in a sustainable fashion.

Furthermore, as the field of FinTech progresses and transforms the financial industry, there is an increasing demand for collaboration and sharing of knowledge across different disciplines (Rizvi et al., 2024). To effectively tackle emerging challenges and fully utilize the potential of FinTech innovations, researchers, policymakers, and industry stakeholders can collaborate and integrate the fields of finance, technology, and regulation. Collaboration among academia, industry, and government entities can expedite the creation of inventive solutions, regulatory structures, and educational programs that encourage responsible innovation, safeguard consumers, and enhance the overall stability of the FinTech ecosystem (Lu, 2024). Hence, this research not only enhances the scholarly comprehension of FinTech's influence on evaluating credit risk and promoting financial inclusion, but also acts as a catalyst for wider deliberations and partnerships focused on shaping the future of finance in an evolving digital age.

The paper is organized as follows: Section 2 discusses background and related work on conventional credit traditional methods, FinTech credit scoring innovations and research gaps in the research. Section 3 elaborates on the proposal of research framework and methodology. Followed by Section 4 presents the expected outcomes and result findings. Section 5 discusses on interpretation of results, comparison with existing literature, implications of the findings and limitations of the study. Finally, Section 6 concludes with a summary of the research.

2. LITERATURE REVIEW

In recent years, the credit scoring and lending practices have undergone substantial changes due to the emergence of FinTech companies and the incorporation of data analytics and machine learning algorithms. The purpose of this section is to examine the current body of literature that offers understanding into the convergence of FinTech, data analytics, and credit scoring.

2.1. Traditional credit scoring methods

Historically, credit scoring has largely been based on historical data, typically sourced from credit bureaus and traditional banking systems (Markov et al., 2022; Bai et al., 2016). Traditional models of credit scoring are too dependent on financial history from sources like credit card usage, borrowing repayment history, and levels of income, which might not correctly determine the creditworthiness of a person or his/her true financial ability. These could be biased against young people, immigrants, and generally those with low access to credit, preferring those who have already been able to build credit reputations. Traditional credit-scoring models tend to miss other possible alternative signs of creditworthiness, including rental payments, utility bill payments, and educational achievements, and thus provide faulty risk assessments that could shut out deserving borrowers. Traditional credit-scoring methods may also be slow in adapting to changes in financial behaviour or economic fortunes and are hence limited in their ability to predict credit risk accurately in dynamic environments (Toh, 2023). A strict reliance on traditional credit-scoring methods will also further marginalize the deprived sections of the population from access to financial services and constrict their economic opportunities (Markov et al., 2022).

Traditional models are agreed to have been crucial, to date, in assessing the creditworthiness of borrowers and in considering risks from a lender's perspective in the financial system. However, they inherently possess one limitation or another since they cannot even include sources of non-traditional data. As stated by Bai et al. (2016), this very narrow scope ensures that the financial health and behaviour of individuals cannot be thoroughly assessed. Traditional credit scoring models do not have access to information provided by alternative data sources, such as social media activity, e-commerce transactions, and utility payment histories. In this regard, the financial industry is increasingly acknowledging that traditional methods for credit scoring must be merged with more comprehensive and dynamic approaches to enhance the level of accuracy in predictions, along with a better understanding of risk management capabilities (Markov et al., 2022).

Due to several disadvantages associated with traditional credit scoring models, there has been a recent surge of interest in the use of machine learning algorithms in the revamping of credit rating practices in the FinTech industry (Bai et al., 2016; Shi et al., 2022). Machine learning techniques are beneficial in that they can cope easily with volumes of high volumes of different types of data and may find important patterns and relationships that might be out of the reach of traditional models. Shi et al. (2022) indicate that the machine learning algorithms integrate the use of random forests and neural networks while conducting analysis on both structured and unstructured data in delivering credit risk profiles. Possibly, the integration of the alternative data sources into the algorithm, such as digital footprints or behavioral indicators, might carry out an expanded review of the borrowers' creditworthiness, improving lending decisions and reducing the incidence of defaults. In the end, both researchers and practitioners would increasingly agree with the fact that a set of machine learning algorithms integrated with credit scoring practices in FinTech embraces great potential for better lending ecosystems to make them more inclusive and data-driven (Mulyadi & Anwar, 2023; Nene, 2024).

2.2. FinTech credit scoring innovations

The growth of FinTech has proclaimed a new era of credit scoring methodologies that leverage the power of data analytics through digital transformation (Barrdear & Kumhof, 2016; Indriasari et al., 2022; Baskerville et al., 2020; Mulyadi & Anwar, 2023; Nene, 2024). Whereas traditional models have relied mostly on historical financial data, new models take a more integrated approach that considers a wide range of data from social media chatter, e-commerce transactions, and even the use of smartphones (Barrdear & Kumhof, 2016; Addy et al., 2024).

There is also the likelihood that the adoption of data-driven credit scoring models by FinTech firms could democratize access to financial services and improve financial inclusion (Baskerville et al., 2020). This class of FinTech can accelerate the pace of the credit evaluation process using machine learning algorithms, reducing the red tape and paperwork that may come with seeking credit (Sadok et al., 2022). By considering a wider range of sources, including traditionally under-served segments' information, such as gig economy workers or those with limited credit history, FinTech firms are expanding the circle of credit access to usually marginalized groups (Markov et al., 2022). Therefore, the rise of credit-scoring models driven by FinTech allows the potential to make significant contributions to more increased levels of financial inclusions and extended economic opportunities for both individuals and businesses.

Besides, improving FinTech credit scoring increases the accuracy and predictability of credit ratings. The models, with the help of machine learning and AI techniques, can recognize complex patterns and correlations in large data — which may not be possible using traditional methods of scoring (Demma Wube et al., 2024). With an elaborate study, it is possible for FinTech firms to filter out the borrowers into good credit and high-risk segments so that probable risks can be better assessed and defaults reduced, perhaps. Besides, iterative machine learning algorithms enable these models to learn constantly and adapt to changes in the market environment, which usually means performance improves with time and enhances stability in lending portfolios. The opposite side of this coin is that data-driven credit scoring models raise concerns about data privacy protection, process transparency, and algorithmic bias problems.

This could be data from social media activities or smartphone use that may raise concerns of privacy on the part of consumers who may or may not have been fully informed about how their information has been gathered and used in the credit evaluations (Quach et al., 2022). Besides, poor transparency of machine learning algorithms would make explanations about the factors affecting credit decisions issues (Addy et al., 2024). This could lead to the extension of existing biases or discriminations. The guiding principles of transparency, accountability, and non-discrimination should be followed by FinTech companies in their credit-scoring methodologies. This way, such innovations can support equitable and non-biased access to credit, without inadvertently perpetuating existing inequalities in systems.

2.3. Research gap and the need for the study: Challenges and concerns

While FinTech credit scoring demonstrates a great deal of promise, it has also raised some concerns which are algorithmic biases may arise, data privacy could be at risk, and there is a proper need for legislative control (Bahoo et al., 2024). Alternative sources of information combined with machine learning methods bear some risks of biased data itself that could give privileged positions to certain groups of the population and reduce the rate of defaults. Yet, despite the fact that these studies have identified the complexity of FinTech credit scoring and associated pros and cons, the in-depth analysis that has compared the effectiveness of FinTech credit-scoring models with more traditional ones is completely lacking. Very few empirical investigations have been conducted thus far on whether the adoption of alternative data sources and data analytics in FinTech reduces credit risk assessment compared to traditional credit scoring models (Agarwal et al., 2019).

In addition, since the recent growth and evolution of the FinTech industry, it is of critical importance to consider the more general implications of FinTech credit scoring. It would range from impacts on financial inclusion to the potential for providing credit access to poorer populations, and all issues that come with ensuring non-discrimination and managing the risks (Agarwal et al., 2019). This implies a clear need for policymakers, regulators, and financial institutions to investigate FinTech developments. It acts as a guide and assists them in negotiating the complicated scenarios suitably (Sunil et al., 2019).

This study, therefore, tries to fill the gaps in the literature by comparing traditional and FinTech credit scoring techniques and assesses how such ideas influence risk control and financial inclusion. The contribution here adds to the already existing knowledge base and forms a significantly enlightening guidance for companies negotiating the changing landscape of credit scores in the FinTech era. The rapid rise of FinTech credit scoring systems further makes the environment dynamic and requires constant processing and judgment. How these new machine learning algorithms and sources of data coming up will eventually influence the modes of credit assessment is required to be continuously monitored. This very ability for scale and integration with multiple FinTech credit scoring solutions has raised a host of challenges in trying to maintain comparable and consistent credit ratings across multiple platforms and jurisdictions. These challenges underline the need for continued research and collaboration among individuals and organizations engaged in forging the best methods, regulations, and institutional frameworks that foster innovation while protecting consumer rights and therefore sustaining overall stability.

The widespread use of FinTech credit scoring models raises important questions about algorithmic biases, data security, transparency, accountability, and customer insight (Nobanee et al., 2024). The feeling of lack of confidence and uncertainty arises from the fact that consumers have inadequate knowledge about the techniques applied to attain, examine, and employ data to ascertain the creditworthiness of a person. Besides, non-transparency in the machine learning techniques leads to non-justifiability of credit choices, hence undermining customer confidence, and regulatory control may be weakened (Schmitt, 2024). Hence, in the future, research will have to shift from mere assessment of predictive accuracy and risk-reducing capacity of FinTech credit-scoring models to more general issues of transparency, comprehensibility, and consumer empowerment if ethical and responsible use of these technologies is to be guaranteed.

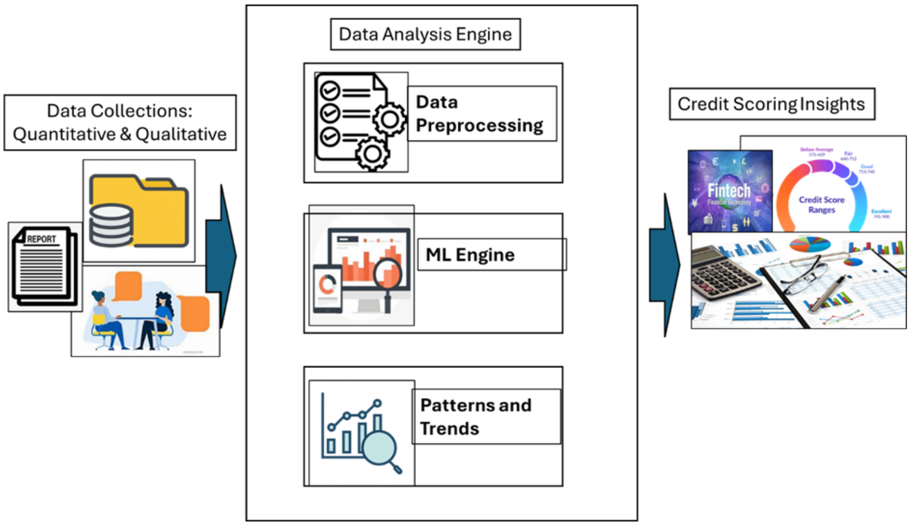
3. METHODOLOGY

This research utilizes a hybrid approach, integrating quantitative analysis and qualitative insights to thoroughly investigate credit scoring practices in both traditional financial institutions and FinTech firms. The study employs statistical techniques and machine learning algorithms to quantitatively evaluate the efficiency of credit scoring models. Additionally, we conduct qualitative interviews with industry experts to obtain detailed insights into the practical application and obstacles of these models. The study's objective is to suggest a comprehensive comprehension of credit assessment practices and their consequences in modern finance.

3.1. Research design

This study uses a mixed-method research design in which quantitative and qualitative methodologies will be combined to carry out an elaborate analysis of credit-scoring practices in traditional financial institutions and FinTech enterprises. The proposed approach will be applied to systematic comparison analysis of the effectiveness and accuracy of credit-scoring models used in organizations. The accuracy, precision, and default rate will be quantitatively estimated using statistical methods and machine learning algorithms for the different classes of credit scoring models. An in-depth of the research methodology that will be employed throughout the course of this research consists of three major components: the data collection module, data analysis engine and credit scoring insights, as shown in Figure 1.

Figure 1. Conceptual research methodology framework



In the selection of the mixed-method approach, several competing research designs were considered as alternatives to test their appropriateness for the research study as alternative research designs. Firstly, purely quantitative analysis, which would retain only the statistical and machine learning-based assessments in testing the performance of the models. While this holds immense empirical value, such a study would have to give up important insights into the practical and ethical challenges of real-world applications because it would not cover industry expert opinions. Secondly, only qualitative approach, which focuses on purely qualitative data from expert interviews, one might investigate deep into those specific challenges for the industry and the contextual factors affecting these. This would lack quantitative robustness for direct comparison between model performances. Thus, generalization of findings and validation of predictive accuracy of models are seriously constrained. The mixed-method approach was thus chosen, given the limitations of each alternative, to balance quantitative rigor with qualitative depth in pursuit of holistically understanding credit scoring practices. This approach provides reliable empirical metrics while integrating insights from industry professionals and offers a well-rounded perspective on both the technical effectiveness and practical challenges of credit-scoring models.

Figure 1 presents an elaborate visual representation of the research methodology used in this study. It illustrates the key components, including the data collection module, which involves gathering relevant information from various sources in a systematic manner. The data analysis engine is responsible for analysing and synthesising the raw data to generate meaningful insights. Lastly, the credit scoring insights module extracts the rigorous analysis and interpretation into actionable intelligence, providing valuable decision-making support for credit assessment and risk management.

The development of a robust data analysis engine for FinTech credit scoring utilizing machine learning comprises three crucial elements: data preprocessing, machine learning (ML) engine, and pattern and trends. Firstly, data preprocessing is an essential step in preparing raw data gathered from different sources. This stage commences by collecting a wide range of data types that are relevant to determining creditworthiness, such as financial records and personal information. The gathered data undergoes thorough cleaning and preprocessing to correct errors, discrepancies, and any missing values. This guarantees that the data is standardized and prepared for analysis in subsequent stages.

During the ML engine phase, the attention is directed towards the process of selecting relevant features and developing the model. The preprocessed data is used to determine and choose the most pertinent features for credit scoring. This entails evaluating the influence of each characteristic on predictive models and potentially creating novel characteristics to capture crucial patterns in the data. Subsequently, machine learning algorithms such as logistic regression, decision trees, and neural networks are utilized to train models that acquire knowledge from the data and accurately forecast credit risk.

After performing feature selection, the pattern and trends component is dedicated to analyzing and interpreting the knowledge acquired during model training. This stage requires comprehending the patterns and correlations discovered by the machine learning models. Analysts thoroughly examine the results of the model to discover practical and useful information that can guide decisions related to credit scoring. This phase guarantees that the models not only accurately forecast credit risk but also offer valuable insights into customer behavior and financial trends. Then, the subsequent steps involve evaluating and validating the models to ensure their reliability and performance. This rigorous procedure involves assessing the accuracy of models and evaluating their resilience using validation techniques like cross-validation. By deploying validated models into operational environments and consistently monitoring their performance, the data analysis engine can maintain its effectiveness and adaptability to changing market conditions and regulatory requirements.

In addition to the quantitative analysis, this research includes conducting in-depth interviews with a wide range of industry experts, such as representatives from traditional banks, FinTech firms, regulatory bodies, and consumer advocacy groups. Through these qualitative inquiries, the study aims to obtain detailed and nuanced understanding of the practical implementation, challenges, and implications of credit scoring methodologies in modern finance. These interviews will offer valuable insights into the context, revealing the factors that influence credit scoring practices, perceptions of risk, and the considerations related to fairness and inclusivity in lending decisions. This research design also seeks to provide a comprehensive understanding of the changing credit scoring landscape in both traditional and FinTech-driven financial ecosystems by combining quantitative data analysis with qualitative insights.

3.2. Data collection

The main source of quantitative data for this study will be a comprehensive dataset that includes credit information from both traditional banks and FinTech lenders. This dataset will include a diverse range of variables, such as credit scores, demographic characteristics, loan repayment histories, and information about the credit scoring models used by these institutions. In addition, we collect additional data pertaining to market trends and regulatory frameworks that impact credit scoring practices.

Qualitative data will be collected by conducting semi-structured interviews with experienced professionals from various areas of the financial industry, such as credit analysts, data scientists, regulatory experts, and industry stakeholders. The purpose of these interviews is to gather detailed accounts and direct viewpoints on the practical application of credit scoring models, as well as their influence on lending choices and the financial experiences of consumers.

The quantitative data will be obtained from various sources, such as publicly accessible datasets, exclusive information from well-established financial institutions, and cooperative agreements with specific FinTech companies. By combining data from various sources, we ensure the strength and thoroughness of our analytical framework. Qualitative data, however, will be systematically collected through interviews with individuals who have extensive knowledge and practical experience in credit scoring methodologies and lending practices in both traditional banking and FinTech industries.

Moreover, the process of selecting data samples, which will include both quantitative and qualitative data, will be intentionally carried out to ensure that they are representative and allow for a thorough analysis. By utilising a stratified sampling technique for quantitative data, we can obtain a well-balanced representation of both the traditional banking and FinTech sectors. This will allow us to make meaningful comparisons between the two. Purposive sampling will be used to select and involve experts with diverse backgrounds and perspectives for qualitative interviews. This approach will enhance the qualitative analysis and offer nuanced insights into the subject matter.

3.3. Data analysis techniques

The quantitative data collected in this study will be subjected to rigorous analysis, utilising a variety of statistical and machine learning methods specifically designed to produce comprehensive insights. These techniques encompass descriptive analysis, which first provides a summary and visualisation of important variables, such as credit scores, loan repayment behaviour, and demographic attributes, to provide a comprehensive understanding of the dataset. Subsequently, statistical tests will be employed to conduct a comparative analysis to identify significant differences in accuracy, efficiency, and risk assessment between credit scoring models employed by traditional financial institutions and FinTech entities. Furthermore, machine learning models, which include algorithms such as logistic regression, decision trees, and neural networks, will be used to forecast creditworthiness using the collected data. The models' effectiveness will be carefully assessed using relevant metrics like accuracy, precision, and recall. The process of analysing quantitative data will be made easier by using sophisticated statistical software packages such as R and Python. These software packages offer powerful features for manipulating, visualising, and modelling data.

Additionally, qualitative content analysis will be conducted on the interview data to identify significant themes, patterns, and insights found in the interview transcripts. This qualitative analysis will provide essential context to understand the complex aspects of credit scoring in both sectors. To collect qualitative data, a carefully designed semi-structured interview protocol will be used to direct conversations with industry experts. This protocol, consisting of open-ended questions, will effectively capture nuanced perspectives on credit scoring practices, challenges, and potential benefits.

3.4. Ethical considerations

This study is expected to set a high importance on ethical standards throughout every step of its implementation. Before starting the interviews, we will make sure to obtain explicit informed consent from all participants. This means that we will ensure that they fully understand the objectives of the study and their rights as contributors. Stringent measures will be put in place to protect the privacy and confidentiality of data, which will involve careful anonymization or pseudonymization of personally identifiable information and strict adherence to protocols for secure data handling and storage.

Moreover, a commitment to reasonable and unbiased analysis will emphasise the entirety of the data evaluation process. Utmost care will be taken to avoid any partiality or preference during the analysis of data, guaranteeing that results are reported in an unbiased manner, irrespective of their conformity with initial hypotheses. The study has received ethical review and approval from the Institutional Review Board and Research Ethics Committee, indicating adherence to established ethical guidelines and regulations to protect the well-being and rights of all participants and stakeholders. The combination of ethical considerations and rigorous data analysis methods ensures the integrity and credibility of findings when evaluating credit scoring methodologies in both traditional financial and FinTech sectors.

4. EXPECTED OUTCOMES AND RESULTS

From the proposed analysis, this study presents a comprehensive analysis of credit scoring methods used by both traditional financial institutions and FinTech companies. It combines quantitative and qualitative data to offer detailed insights into their effectiveness and consequences. The study commences by presenting an analysis of the performance of credit scoring models. It then examines their accuracy, efficiency, and ability to assess risk in both traditional banks and FinTech firms. The performance levels of these models are explained using quantitative measures and visual representations, providing a comprehensive understanding of their effectiveness (Markov et al., 2022).

Subsequently, a thorough examination is carried out to compare the credit scoring models used in traditional banking and FinTech lending platforms. This segment thoroughly analyses important distinctions and similarities, specifically emphasizing critical factors such as model precision, effectiveness, and risk evaluation. Quantitative measures and statistical analyses shed more light on the relative strengths and weaknesses of these models, offering valuable insights into their individual contributions to predicting creditworthiness and managing risk (Addy et al., 2024).

Finally, the study examines the wider consequences of credit scoring techniques on both financial inclusion and risk management. This study investigates whether credit scoring models driven by FinTech facilitate increased financial inclusion by providing credit access to marginalized populations. It evaluates the risk management difficulties and potential advantages associated with both conventional and FinTech credit scoring methods. The study provides valuable insights into the changing credit assessment landscape by thoroughly examining these aspects. This empowers stakeholders with informed decision-making tools to navigate the complexities of credit scoring methodologies in both the traditional banking and FinTech sectors

5. DISCUSSION AND SUMMARY

5.1. Interpretation of results

The results obtained in this study offer enough insight into how credit scoring methods are effective in both traditional financial institutions and FinTech companies. Using data sources, algorithmic complexity, and operational frameworks to base its review on, this research has found some convincing differences in performance between the traditional and FinTech-driven credit-scoring models. Most of these FinTech models leverage alternative data sources coupled with advanced algorithms that appear to pick up distinctions in borrower creditworthiness. The analysis underlines practical implications for both borrowers and lenders, outlining key determinants in each sector that may affect credit accessibility and equity. Second, the results of risk assessment outputs underline that the trade-off between the precision of prediction and the mitigation strategies of risk are indispensable in maintaining financial stability and serving the needs of the borrowers.

5.2. Comparison with existing literature

The paper's contribution is based on the already available literature. Therefore, this research extends the literature by presenting an overall comparative study of credit rating techniques using evolving FinTech. Whereas the literature has focused on specific aspects of FinTech's impact on financial services, this study offers a broad analysis of both operational and ethical dimensions in detail, thus enriching the discussion of credit-scoring practices. For example, while past research has identified how FinTech increases access to credit using alternative data (Cao et al., 2024; Rehman et al., 2023), our results go one step further by underlining practical challenges to ensuring unbiased analyses, especially on algorithmic fairness and regulatory compliance (Truby et al., 2020). In addition, where prior research has pinpointed the relative efficiency of machine learning algorithms in credit assessment, this study builds empirical evidence of algorithms as compared to traditional methods concerning strengths and limitations in accuracy and reliability (Bitetto et al., 2023; Muñoz-Izquierdo et al., 2022). We also highlight how our findings compare with previous studies in the extension of knowledge on strengths and gaps in existing frameworks and encouragement of further research into this dynamic area.

5.3. Implications of the findings

The implications of this finding are multilayered, with various groups of stakeholders involved in the financial industry. On the part of the financial institution and FinTech companies, our findings carry implications for strategies to be adopted for enhancing credit evaluation processes, such as the infusion of responsible AI to mitigate the threat of bias and exclusion in credit-scoring models. These would also be useful to policymakers in developing regulatory frameworks, considering factors for fair and efficient access to credit and transparency in

FinTech-driven credit scoring. Secondly, the attention to algorithmic bias-related risks and higher default rates points to the imperative of responsible innovation in the FinTech industry. In general, these recommendations should be in line with the vision of an inclusive, data-driven, and ethical financial ecosystem where measures are taken toward sustainable growth and fair lending practices.

6. CONCLUSION

The study provides significant insight into both the traditional financial institution and FinTech credit scoring practices, underlining great variance in model performance, operational efficiency, and ways of assessing risk. In fact, these findings reflect the evolution in credit-scoring techniques and how FinTech has been playing a transformative role in terms of extending credit facilities and enhancing financial inclusions, particularly for the deprived sections. This research also contributes meaningfully to the practice and theory of financial services by helping stakeholders adjust their strategies in view of the changing credit-scoring landscape and informs data-driven decisions.

Nevertheless, this research is not without limitations. First, reliance on secondary data sources introduces constraints on completeness and quality issues that may affect the robustness of our analysis. Although the datasets were indeed diverse, accuracies of data may vary which yield variety of outcomes. Secondly, the sample size and composition of our qualitative interviews would also largely constrain the generalizability of insights. The purposive selection of experts helped us, but their views may fail to reflect those from the broader financial industry. Further studies may take these limitations into consideration by expanding the sample size and ensuring that the samples are more diverse to become representative, allowing a wider perspective from different stakeholders.

The fact that it is a comparison is, by far, the main limitation of this credit scoring model study, which may not generalize findings in other regions or sectors with different regulatory and economic environments. Cross-cultural and cross-sectoral variations of credit-scoring practices could provide a fruitful avenue for future studies for an in-depth understanding of credit assessment globally. The present study calls for further research considering the complex challenges that arise from an area of credit scoring in evolution. Future research should, as FinTech is still innovating and remaking financial services, look to see what new technologies are emerging in credit scoring while simultaneously reassessing the long-term impacts of these technologies on financial inclusion and risk management. Moreover, research touching on the issues of algorithmic fairness, regulatory compliance, and ethical concerns in AI-driven credit scoring would further provide the guidance responsible innovation requires. With these contributions to the critical areas, future research will be supportive in fostering a financial ecosystem that focuses on the aspects of fairness, inclusiveness, and efficiency within credit assessments towards sustainable development in the financial services industry.

REFERENCES

Addy, W. A., Ajayi-Nifise, A. O., Bello, B. G., Tula, S. T., Odeyemi, O., & Falaiye, T. (2024). AI in credit scoring: A comprehensive review of models and predictive analytics. *Global Journal of Technology and Engineering Applications, 18*(2), 118–129. https://doi.org/10.30574/gjeta.2024.18.2.0029

Agarwal, S., Alok, S., Ghosh, P., & Gupta, S. (2019). *Financial inclusion and alternate credit scoring: Role of big data and machine learning in Fintech*. Indian School of Business. https://doi.org/10.2139/ssrn.3507827

Al-Afeef, M. A., Alsmadi, A. A., Al-Okaily, M., & Al-Sartawi, A. (2024). The role of peer-to-peer lending platforms in expanding financial inclusion. In A. M. A. Musleh Al-Sartawi & A. I. Nour (Eds.), *Artificial intelligence and economic sustainability in the era of industrial revolution 5.0* (Studies in systems, decision and control). Springer. https://doi.org/10.1007/978-3-031-56586-1_10

Alyaqoot, F., Hamdan, A., & Al Abbas, A. (2022). The impact of Fintech in entrepreneurship development: The moderation role of banking during crisis. In B. Alareeni & A. Hamdan (Eds.), *Financial technology (FinTech), entrepreneurship, and business development* (Vol. 486, pp. 1–10). Springer. https://www.springerprofessional.de/en/the-impact-of-fintech-in-entrepreneurship-development-the-modera/23233066

Bahoo, S., Cucculelli, M., Goga, X., & Mondolo, J. (2024). Artificial intelligence in finance: A comprehensive review through bibliometric and content analysis. *SN Business & Economics, 4,* Article 23. https://doi.org/10.1007/s43546-023-00618-x

Bai, J., Philippon, T., & Savov, A. (2016). Have financial markets become more informative? *Journal of Financial Economics, 122*(3), 625–654. https://doi.org/10.1016/j.jfineco.2016.08.005

Barrdear, J., & Kumhof, M. (2016). *The macroeconomics of central bank issued digital currencies* (Bank of England Staff Working Paper No. 605). Bank of England. https://doi.org/10.2139/ssrn.2811208

Baskerville, R., Capriglione, F., & Casalino, N. (2020). Impacts, challenges, and trends of digital transformation in the banking sector. *Law and Economics Yearly Review Journal, 9*(2), 341–362. https://ssrn.com/abstract=3835433

Bitetto, A., Cerchiello, P., Filomeni, S., Tanda, A., & Tarantino, B. (2023). Machine learning and credit risk: Empirical evidence from small- and mid-sized businesses. *Socio-Economic Planning Sciences, 90*, Article 101746. https://doi.org/10.1016/j.seps.2023.101746

Cao, S., Jiang, W., Lei, L., & Zhou, Q. (2024). *Applied AI for finance and accounting: Alternative data and opportunities*. https://doi.org/10.2139/ssrn.4753640

Demma Wube, H., Zekarias Esubalew, S., Fayiso Weldesellasie, F., & Girma Debelee, T. (2024). Deep learning and machine learning techniques for credit scoring: A review. In T. G. Debelee, A. Ibenthal, F. Schwenker, & Y. Megersa Ayano (Eds.), *Pan-African conference on artificial intelligence* (Vol. 2069). Springer. https://doi.org/10.1007/978-3-031-57639-3_2

Ebirim, G. U., & Odonkor, B. (2024). Enhancing global economic inclusion with Fintech innovations and accessibility. *Finance & Accounting Research Journal, 6*(4), 648–673. https://doi.org/10.51594/farj.v6i4.1067

Harsono, I., & Suprapti, I. (2024). The role of Fintech in transforming traditional financial services. *Accounting Studies and Tax Journal (COUNT), 1*(1), 81–91. https://doi.org/10.62207/gfzvtd24

Indriasari, E., Prabowo, H., Ford, L. G., & Purwandari, B. (2022). Digital banking: Challenges, emerging technology trends, and future research agenda. *International Journal of e-Business Research, 18*(1), Article 12. https://doi.org/10.4018/IJEBR.309398

Kamuangu, P. (2024). A review on cybersecurity in Fintech: Threats, solutions, and future trends. *Journal of Economics Finance and Accounting Studies, 6*(1), 47–53. https://doi.org/10.32996/jefas.2024.6.1.5

Lu, L. (2024). The law of Fintech: How artificial intelligence and innovative technologies contribute to a sustainable financial industry and its effective regulation. In T. Walker, D. Gramlich, & A. Sadati (Eds.), *Artificial intelligence, finance, and sustainability* (pp. 243–263). Palgrave Macmillan. https://doi.org/10.1007/978-3-031-66205-8_10

Markov, A., Seleznyova, Z., & Lapshin, V. (2022). Credit scoring methods: Latest trends and points to consider. *The Journal of Finance and Data Science, 8,* 180–201. https://doi.org/10.1016/j.jfds.2022.07.002

Mulyadi, M., & Anwar, Y. (2023). Machine learning in accounting: Insight from the March 2023 bank failures. *Risk Governance and Control: Financial Markets & Institutions, 13*(2), 28–36. https://doi.org/10.22495/rgcv13i2p3

Murinde, V., Rizopoulos, E., & Zachariadis, M. (2022). The impact of the Fintech revolution on the future of banking: Opportunities and risks. *International Review of Financial Analysis, 81,* Article 102103. https://doi.org/10.1016/j.irfa.2022.102103

Muñoz-Izquierdo, N., Segovia-Vargas, M. J., & Camacho-Miñano, M. D. M. (2022). Machine learning in corporate credit rating assessment using the expanded audit report. *Machine Learning, 111*, 4183–4215. https://doi.org/10.1007/s10994-022-06226-4

Nene, P. R. (2024). Can artificial intelligence replace assurance, governance, and risk management professionals? *Risk Governance and Control: Financial Markets & Institutions, 14*(2), 25–31. https://doi.org/10.22495/rgcv14i2p3

Nobanee, H., Ellili, N. O. D., Chakraborty, D., & Shanti, H. Z. (2024). Mapping the Fintech revolution: How technology is transforming credit risk management. *Global Knowledge, Memory and Communication.* Advance online publication. https://doi.org/10.1108/GKMC-12-2023-0492

Quach, S., Thaichon, P., Martin, K. D., Weaven, S., & Palmatier, R. W. (2022). Digital technologies: Tensions in privacy and data. *Journal of the Academy of Marketing Science, 50*, 1299–1323. https://doi.org/10.1007/s11747-022-00845-y

Rehman, S. U., Al-Shaikh, M., Washington, P. B., Lee, E., Song, Z., Abu-AlSondos, I. A., Shehadeh, M., & Allahham, M. (2023). Fintech adoption in SMEs and bank credit supplies: A study on manufacturing SMEs. *Economies, 11*(8), Article 213. https://doi.org/10.3390/economies11080213

Rizvi, S. K. A., Rahat, B., Naqvi, B., & Umar, M. (2024). Revolutionizing finance: The synergy of Fintech, digital adoption, and innovation. *Technological Forecasting and Social Change*, *200*, Article .123112 https://doi.org/10.1016/j.techfore.2023.123112

Sadok, H., Sakka, F., & El Maknouzi, M. E. H. (2022). Artificial intelligence and bank credit analysis: A review. *Cogent Economics & Finance, 10*(1), Article 2023262. https://doi.org/10.1080/23322039.2021.2023262

Schmitt, M. (2024). *Explainable automated machine learning for credit decisions: Enhancing human artificial intelligence collaboration in financial engineering.* https://doi.org/10.2139/ssrn.4716847

Shi, S., Tse, R., Luo, W., D'Addona, S., & Pau, G. (2022). Machine learning-driven credit risk: A systemic review. *Neural Computing and Applications, 34*, 14327–14339. https://doi.org/10.1007/s00521-022-07472-2

Sunil, M., Prabha, C., & Gupta, M. (2019). Fintech innovations and their impact on traditional financial institutions, payment systems, and financial inclusion: A review of case studies. *International Journal of Research and Analytical Reviews, 6*(2), 21–28. https://www.researchgate.net/publication/373019985_

Toh, Y. L. (2023). Addressing traditional credit scores as a barrier to accessing affordable credit. *Economic Review, 108*(3), 1–22. https://doi.org/10.18651/ER/v108n3Toh

Truby, J., Brown, R., & Dahdal, A. (2020). Banking on AI: Mandating a proactive approach to AI regulation in the financial sector. *Law and Financial Markets Review, 14*(2), 110–120. https://doi.org/10.1080/17521440.2020.1760454

Xie, C., & Huang, L. (2024). How to drive sustainable economic development: The role of Fintech, natural resources, and social vulnerability. *Resources Policy, 94,* Article 105104. https://doi.org/10.1016/j.resourpol.2024.105104

Xie, P., Md Kassim, A. A., Wei, M., & Helmi, R. (2023). The impact of blockchain adoption on financial performance in fintech firms: A review of the literature. *Frontiers in Business, Economics and Management, 11*(2), 302–305. https://doi.org/10.54097/fbem.v11i2.12627

Xu, Y., Liu, Y., Xu, H., & Tan, H. (2024). AI-driven UX/UI design: Empirical research and applications in Fintech. *Academia Nexus Journal, 3*(1). https://academianexusjournal.com/index.php/anj/article/view/6