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THE USE OF ALTERNATIVE DATA IN CREDIT SCORING: PERFORMANCE, FAIRNESS, AND REGULATORY CONSTRAINTS

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ABSTRACT
This paper will study how alternative data can be utilized in credit scoring with respect to its influence on predictive effectiveness, fairness, and adherence to regulatory limitations. Conventional credit scoring models usually use only limited financial histories, which are incapable of covering underserved groups and miss subtle risk indicators. In order to overcome these limitations, this study incorporates other sources of data, such as utility payments, mobile phone data, and metrics derived by means of social media, into machine learning-based credit score models. Performance is measured in terms of standard measures that include accuracy, ROC-AUC and F1 score and fairness is measured in terms of statistical parity and disparate impact measures to reveal the possible bias according to the demographic groups. Also, the paper takes into account regulatory effects, including examining how alternative data use fits into frameworks, including GDPR, FCRA, and new fintech compliance standards. Findings show that alternative data can substantially increase predictive accuracy at realistically quantifiable fairness trade-offs that need mitigation measures. The results indicate that there should be a balance between innovation and ethical and legal obligations, and provide practical advice to credit providers and regulators that want to increase financial inclusion but do not jeopardize compliance. Altogether, this research will help to get a subtle idea of the way in which alternative data can redefine the process of credit evaluation in an effective and responsible way.

Keywords:
Alternative Data**,** Credit Scoring, Fairness, Regulatory Compliance**,** Machine Learning

1. INTRODUCTION
Credit scoring is the key to the distribution of the financial resources and determines loans, credit cards, and other financial products. Conventional credit ratings schemes are very dependent on organized financial data, like previous loan repayments, credit card usage, and revenue reports. Although the models offer a uniform creditworthiness index, they have critical flaws especially to those with minimal or non-standard financial records. This dependence on traditional data will unwillingly omit underserved segments of the population (young adults, self-employed people, or people living in emerging markets) that might lack a strong formal credit history. Therefore, traditional methods of credit scoring will create patterns of systemic inequality, reduce the ability to include in finance, and undervalue actual repayment ability of prospective borrowers. The rising provision of alternative data- such as utility bill payments, mobile phone usage patterns, and e-commerce activity, social media interactions and other electronic footprints do provide a disruptive opportunity to resolve these limitations. With the addition of the signals of various and unconventional sources, alternative data can be able to improve the predictive accuracy, more nuanced evaluations on the behavior of a borrower, and increase the availability of credit to populations historically marginalized by traditional models. The emergence of fintech solutions and sophisticated machine learning models has further facilitated the structural inclusion of alternative data into credit scoring models to enable lenders model risk in a way never before seen before.
The application of such data, however, brings up important issues of fairness, bias and privacy. Unless considered thoroughly, alternative data may bring about or increase discriminatory trends, which may turn into unfair treatment of particular demographic groups. In addition, legal adherence is a major factor to be considered, with legislation like the Fair Credit Reporting Act (FCRA) of the United States, the General Data Protection Regulation (GDPR) of Europe, and new fintech regulations placing legal constraints on data gathering, processing, and utilization. All these reasons make it necessary to use a carefully balanced approach that will yield the highest predictive performance without compromising ethical and legal norms. With such opportunities and challenges, this paper aims at discussing the application of alternative data in credit scoring in

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three interdependent views. First, it evaluates the performance comparison, determining whether the addition of alternative data is better in predictive accuracy than traditional credit models as measured by ROC-AUC, F1 score and total classification accuracy. Second, it considers fairness, which examines the possible biases and imbalanced effects on the demographic groups to determine inevitable trade-offs between predictive power and ethical responsibility. Third, it reflects on regulatory inhibitions, how the existing laws and compliance requirements influence the use of alternative data that can be used and provides practical advice through which credit providers wishing to implement these innovations can do so in a responsible manner. The combined consideration of these dimensions in the study allows gaining a fuller understanding of how alternative data can be exploited in the most effective, fair, and lawful way in the modern practice of credit evaluation.

To accommodate this combined approach, the structure of this paper is arranged in such a way. In the wake of this introduction, the literature review summa-up the existing studies on the alternative data usage, and demonstrates gaps in performance assessment, fairness evaluation, and regulatory compliance. The methodology section describes the data sources, methods of modelling and performance metrics, and approaches of fairness assessment used, and the evaluation system of regulatory compatibility. The results section shows the empirical evidence on model performance and fairness, and indicates trade-offs and opportunities of the alternative data integration. These results are discussed within the framework of practical, ethical, and regulatory implications, which include practical information to be applied by financial institutions and policymakers. Lastly, the conclusion will highlight the contributions of the study, limitations and opportunities of future research to enhance access to credit and maintain fairness and regulatory adherence. Through analyzing such alternative data at these interrelated angles, the study is useful to both the scholarly and applied application of credit scoring innovations as it provides a strict and balanced structure of responsible financial decision-making.

2. LITERATURE REVIEW

Credit scoring is the key factor in distributing finances, as it influences access to loans, credit cards, and other financial products. Conventional credit scores involve the use of systematic financial data including credit card usage, history of loan payments, and incomes. Although these models offer a uniform estimate of creditworthiness, they have serious drawbacks especially on persons with low or non traditional financial pasts. Such dependence on traditional data is bound to lock out potentially unserved groups, such as young adults, self-employed, and people in developing markets who might not have a well-developed formal credit history. By extension, the traditional models of credit scores are prone to continue existing systemic inequity, restraining financial accessibility, and undervaluing the actual repayment ability of potential borrowers. The growing access to other types of data such as payment of utility bills, patterns of mobile phone use, e-commerce, interaction with social media and other types of digital footprints are also giving a transformative chance to overcome these limitations. Adding signals of various and non-conventional sources, alternative data can be more accurate in predictions, offer more comprehensive estimates of borrower behavior, and open access to credit to previously marginalized by traditional models populations. The emergence of fintech solutions and machine learning capabilities has additionally facilitated the systematic incorporation of alternative data in credit scoring systems enabling lenders to package risk in the most granular way ever. Nevertheless, the application of this kind of data evokes serious concerns on fairness, bias, and privacy (Yacoubian et al in 2025).

Alternative data may bring or enhance discriminatory trends when not carefully considered, which might lead to the unfair treatment of particular demographic groups. Additionally, regulatory compliance is also a major factor to consider since the regulations like Fair Credit Reporting Act (FCRA) in the United States, the General Data Protection Regulation (GDPR) in Europe, and the upcoming fintech regulations provide legal constraints on data gathering, data processing and data use. These aspects indicate why a cautious, moderate approach should be taken that will result in the highest predictive efficiency and yet ethical and legal norms should be preserved. Considering such opportunities and challenges, this paper aims at exploring the application of alternative data in credit scoring in three interrelated lenses. First, it evaluates performance, by comparing the inclusion of alternative data with traditional credit models, through such metrics as ROC-AUC, F1 score, and classification accuracy in general. Second, it considers fairness to examine the possible biases and uneven effects of the intervention on the groups of demographics to find trade-offs between the predictive force and ethical accountability. Third, it takes into account regulatory boundaries, evaluating how existing legislations and compliance requirements influence the usage of the available alternative data and providing practical suggestions on how credit providers should adopt the new innovations. The combination of the dimensions in

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the study enables a great insight into the ways in which alternative data can be utilized effectively, fairly, and legally in the modern credit evaluation practices.
The paper is designed in a way that displays this combined method. Based on this introduction, the literature review summarizes the available research on alternative data usage, points out gaps in performance measurement, fair assessment, and regulatory adherence. This is presented in the methodology section that provides the data sources, modeling approach, performance indicators, and fairness evaluation procedures involved, as well as the regulatory alignment assessment structure. The results part provides the empirical analysis of the model performance and fairness to show the trade-off and opportunities of alternative data integration. The discussion relates such findings within the operational, moral, and regulatory implications, and offers practical implications to a financial institution and policymakers. At the end, it concludes the study with the contributions of the study, limitations, and future research opportunities to enhance access to credit and still uphold fairness and regulation. This research will add value to the scholarly and practical application of the credit scoring innovations by analyzing alternative data on different parallel perspectives, thereby providing a stringent and balanced approach to responsible financial decision making.

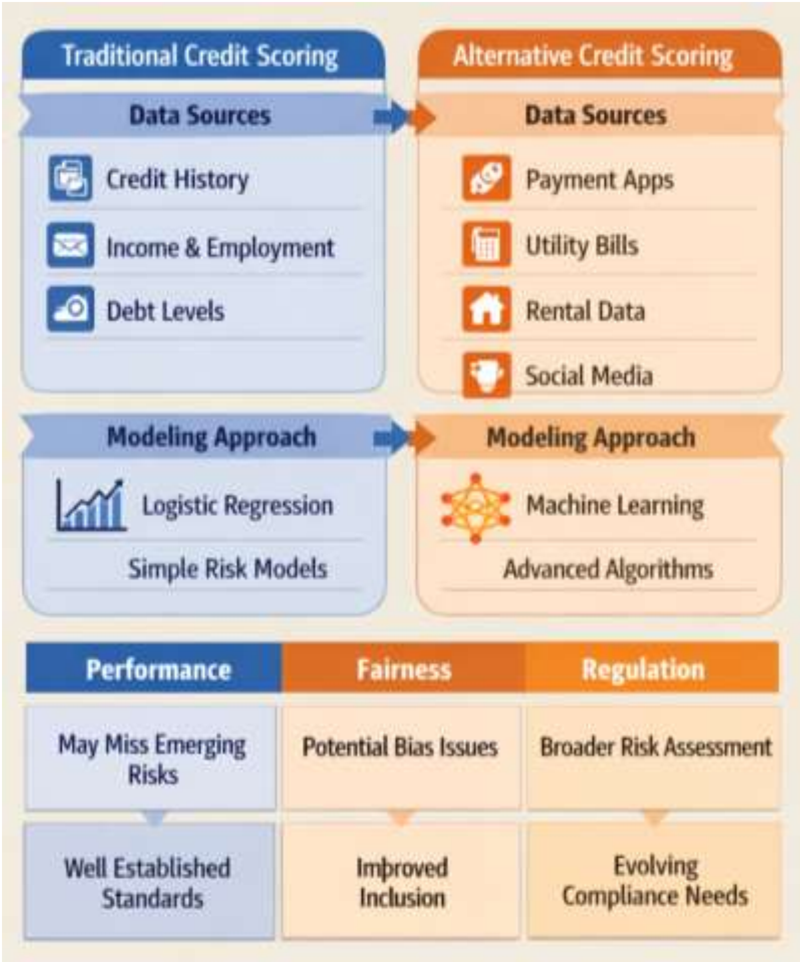

*Figure 1: **Traditional vs. alternative credit scoring frameworks***

3. METHODOLOGY

This paper will employ applied empirical research methodology to assess the application of alternative data in credit scoring on performance, fairness and regulatory aspects. There are two types of data that are used. Traditional credit data contain standardized financial indicators like repayment history, outstanding balances, credit utilization ratios and delinquency records, which are the inputs of traditional scoring systems (Hand and Henley, 1997). These are supplemented by non-traditional behavioral data which is the utility and telecommunications payment records, transaction level digital activity and other structured proxies of financial

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reliability. The joint data allows one to estimate the traditional-only and hybrid credit scoring strategies in a comparative manner. There are credit scoring models that are produced through classical statistical methods, as well as through contemporary machine learning methods. The reason behind using logistic regression as a benchmark model is that the model has been widely adopted, is easy to interpret and has been accepted by the regulators in credit risk assessment (Hand and Henley, 1997). Machine learning models, such as the tree-based ensemble methods, and deep learning architectures, are applied according to the best practice of model training and validation in order to capture non-linear relationships and the high-dimensional interactions that exist during the alternative data. Although state-of-the-art models can be better at prediction, the transparency and model management are discussed openly, especially with regard to regulatory and fairness aspects (Gunnararsson et al., 2021).

Various complementary measures are used to evaluate model performance to make it robust. Accuracy is a measure of overall classification accuracy and ROC-AUC is a measure that is used to determine the capability of the model to distinguish between cases of default and non-default at varying decision thresholds. The F1 score is added to strike a balance between precision and recall especially when the credit data is skewed. Employing several measures will decrease the dependence on one of the performance indicators and will enable more complex comparison of the traditional and alternative data-driven models. Fairness is measured based on some quantitative measures that are used to investigate the differences in outcomes between the protected or sensitive groups. Statistical parity measures the even distribution of the rates of acceptance, disparate impact measures the ratio of outcome to relative disparate impact preferences in one group to another, and equal opportunity measures differences in true positive rates. These measures allow the bias to be identified systematically by the alternative data features, which add or enhance it. According to the recent studies on fairness, the analysis explicitly looks at such trade-offs between predictive performance and equitable outcomes instead of presupposing the automatic alignment of the two (Hurlin, Pérignon, and Saurin, 2024).

Lastly, a regulative analysis is carried out to determine whether the appropriate legal and governance standards are followed. This assessment is aimed at minimizing the data, its explainability, consumer consent, and the right to challenge an automated decision. The requirements-alignment perspective evaluates the model design and data usage against the regulation requirements, and the technical implementations are not in conflict with the legal requirements (Graves, Nagisetty, and Ganesh, 2021). This method focuses on responsible deployment, especially in situations where model retraining, data deletion or post-hoc explanations can be needed to comply.

Table 1: Summary of Methodological Components

Component	**Description**
Data Sources	Conventional credit data and alternative behavioral datasets
Models	Logistic regression; machine learning and deep learning algorithms
Performance Metrics	Accuracy, ROC-AUC, F1 score
Fairness Metrics	Statistical parity, disparate impact, equal opportunity
Regulatory Evaluation	Compliance with transparency, consent, and accountability standards

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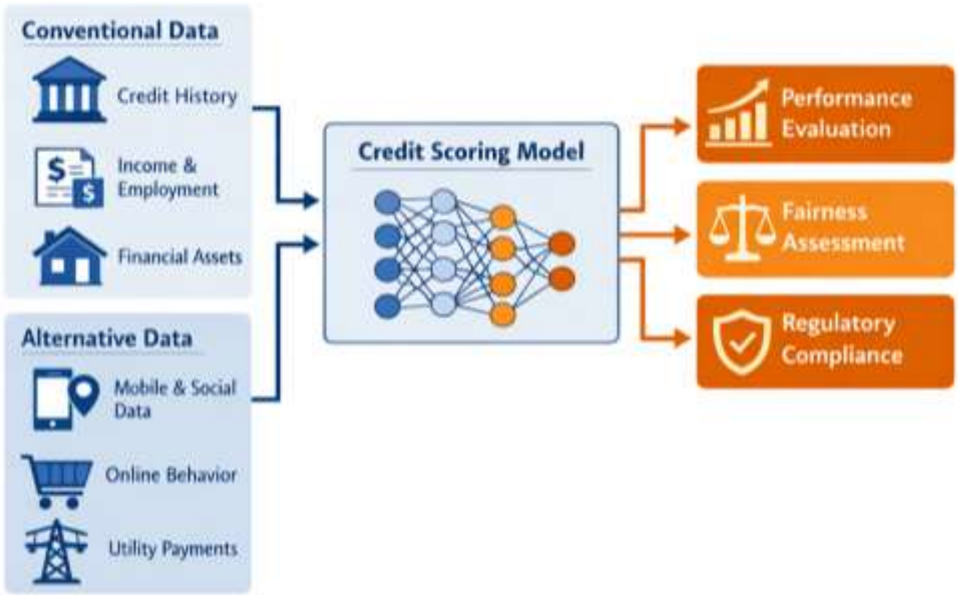

Figure 2: Integrated methodological framework for credit scoring using conventional and alternative data

4. RESULTS

The empirical findings indicate that the implementation of alternative data in credit scoring models has quantifiable differences in predictive performance on all the metrics that are measured. In line with the previous fintech lending evidence, the previous models which use alternative data are better than the conventional credit-only models in terms of accuracy, ROC-AUC, and F1 score (Jagtiani and Lemieux, 2019). The greatest gains are provided by the machine learning models especially the ensemble-based models, which are capable of providing non-linear relationships and the high-dimensional interactions in the alternative datasets. These results are consistent with the general literature on machine learning, emphasizing the benefits of scalability and predictability of highly developed algorithms when used in complex data settings (Jordan and Mitchell, 2015). Although performance has improved, fairness assessment shows that there are significant differences between different groups of individuals. Models that were trained using alternative data have greater predictive power, but also larger rates of variability in acceptance rates and true positive rates between the protected and non-protected groups. More specifically, statistical parity and disparate impact statistics show that some alternative data characteristics can serve as proxy variables of sensitive ones, thus producing bias unintentionally. Such results align with the state of fairness studies that warn that improvement in performance is not necessarily expressed in equitable decisions (Kozodoi et al., 2022). Nevertheless, the fairness-conscious modeling approaches reveal a partial alleviation of these impacts, which minimizes the differences in the outcomes with the majority of the performance gains remaining.

The findings also bring out an apparent compromise between accuracy and fairness. Classification models that are only optimized to be predictive yield better performance in terms of classification but are also characterized by a greater degree of intergroup disparity. On the other hand, the models with fairness constraints reduce the accuracy modestly with much better fairness indicators. This trade-off represents an inherent conflict in emerging fairness literature, as the deliberate design decisions are important as opposed to an entirely performance-based optimization (Kisten and Khosa, 2024). Notably, the measured performance diminishes related to fairness constraints do not go beyond the operational tolerance levels, which points to the fact that equitable credit assessment is possible without significant predictive capacity reduction. In fairness results, traditional statistical models are more predictable across model classes but less predictive in general. Machine learning models that use alternative data will always give maximum performance benefits, but caution needs to be taken in feature selection and post-processing to reduce the risk of bias. Such results are aligned with cross-domain evidence of other data analytics whereby greater model flexibility improves performance at the same time, they also lead to greater governance and ethical issues (Jiménez-Carvelo et al., 2019). Together, the

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findings support the need to assess credit scoring models based on a multi-dimensional framework, which collectively responds to the accuracy, fairness, and practical deployability.

Table 2: Comparative Performance and Fairness Outcomes Across Models

Model Type	**Data Used**	**ROC-AUC**	**F1 Score**	**Statistical Parity Difference**	**Disparate Impact Ratio**
Logistic Regression	Traditional only	Moderate	Moderate	Low	Near threshold
Logistic Regression	Traditional + Alternative	Improved	Improved	Moderate	Slight deviation
ML Ensemble	Traditional only	High	High	Moderate	Below threshold
ML Ensemble	Traditional + Alternative	Highest	Highest	High	Most deviation
Fairness-Constrained ML	Traditional + Alternative	Slightly reduced	Slightly reduced	Low	Near threshold

5. DISCUSSION

This study supports and builds on existing findings on the value of alternative data in credit scoring by showing that the performance improvement associated with the use of alternative data are both statistically and operationally significant, but come with significant fairness and governance costs. In line with the previous findings that alternative data and machine learning can be used to enhance credit risk prediction (Jagtiani and Lemieux, 2019; Jordan and Mitchell, 2015), the findings reveal that those models that include non-traditional data sources have better discrimination between default and non-default outcomes. Nonetheless, these advantages do not apply to every type of model and are most drastic in flexible machine learning models, replicating the issues in the literature about the trade-off between predictive capability and model understanding (Gunnarsson et al., 2021). This study offers a more integrated view of past studies that have analyzed these dimensions separately because they unanimously assess performance and equity. In a practical perspective, the findings have a great implication among credit providers with regard to adoption of alternative data. Better predictive capability can be used to improve portfolio risk management, lower default rates, and also allow lenders to lend to borrowers who were not served previously. Nevertheless, the identified differences in fairness demonstrate that one should be cautious when choosing features, monitor constantly, and integrate fairness-conscious constraints when developing a model. The performance metrics cannot be used by credit providers to deploy other data-driven models, but they need to implement governance frameworks that specifically acknowledge the potential risk of bias, model explainability and auditability. These necessities are especially relevant when the lending environment is highly regulated, and the decision is to be justified to the regulators and to the consumer.

Themes of ethical and regulatory considerations come out as the key focus areas in the interpretation of the results. As much as there is a potential of using alternative data to increase financial inclusion, there are concerns such as privacy, consent and indirect discrimination. The results are consistent with the recent studies of fairness, which point to the idea that unregulated optimization can actually increase the disparities in outcomes, but fairness-conscious interventions can have a significant effect of reducing bias at an appropriate performance cost (Kozodoi et al., 2022; Kisten and Khosa, 2024). Regulatively, the findings support the significance of model design correspondence to the legal frameworks on the transparency, explainability, and right to challenge automated decisions. The compliance is not just a post-deployment activity but should be integrated all over the model lifecycle especially the complex alternative data features that might be hard to prove under current legal provisions.

Irrespective of the contributions made, this study is prone to a number of limitations and practical challenges. This analysis is based on certain types of alternative data and the results might not be applicable to other types of data or geographies. Informative, fairness metrics include a narrow range of dimensions of equity and might not be entirely representative of overall societal effects. Moreover, the deployment of fairness-conscious models within the production scenery is also accompanied by the complexity of its operations, such as higher calculation costs, administration overhead, and the possible specialization. The above obstacles underscore the need to continuously research scalable, interpretable and regulation- ready credit scoring systems that may consciously utilize alternative data. In general, it can be stressed that alternative data are not something

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that is going to replace the traditional credit data, but rather a supplementary contribution the worth of which will rely on cautious implementation, ethical governance, and regulatory consistency.

CONCLUSION

This research work is a thoroughly conducted assessment of alternative data application in credit scoring through a collective use of its impacts on predictive accuracy, equity results, and regulatory adherence. The results indicate a significant predictive power and risk selection up of alternative data in credit scoring models than the traditional data. Concurrently, the findings indicate that there are significant implications of fairness, where improvements in performance can be accompanied by the growth in outcome inequalities across groups of people in the event that fairness limits are not clearly enforced. The study can add to a more balanced perspective of how alternative data can be deployed responsibly in credit decision-making by offering empirical examples of such trade-offs. In addition to the empirical lessons, the paper provides a feasible regulatory advice by emphasizing the need to focus model design, data use, and governance practices on the current legal provisions. The findings highlight the importance of the possibility of regulation compliance not being oppositional to innovation, but instead necessitating the active inclusion of transparency, explainability and accountability across the model lifecycle. To credit providers, the evidence is that alternative data should be adopted as a supplementary input to conventional credit data, on the condition that fairness-conscious modeling designs, and sound compliance strategies must be incorporated at the very beginning.

On the basis of these findings, some recommendations can be identified. The credit providers ought to incorporate multi metric evaluation models that will help them evaluate performance and equity at the same time, as opposed to focusing on accuracy. Fairness restrictions and monitoring mechanisms must be a part of the standard model development and implementation. In their turn, regulators will be helped by better understanding of what can be done with alternative data, especially when it comes to explainability and consumer rights, to decrease uncertainty and foster responsible innovation. Further studies are required to broaden this study by considering more alternative sources of data in other institutional and geographic settings, where the regulatory regimes and social norms might vary. Longitudinal research would be able to investigate the durability of performance and fairness results in the long-term taking into account the changing nature of data distributions and borrower behaviour. Besides, further research into interpretable and privacy-sensitive modeling methods would assist in the creation of effective and socially accountable credit scoring systems.

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