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Research Article

Role of Alternative Data in Ascertaining Credit Eligibility and Reducing Possibility of Fraud

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The increasing speed of digitalization of transactions is generating a greater quantity and variety of consumer data, thereby expanding the store of data that lending institutions can feasibly use to determine the creditworthiness of applicants. In addition, the worldwide proliferation of open financial infrastructures has facilitated data exchange between industries participants, the availability of customer data will increase. Making use of machine learning, a rising quantity of applicant's financial data & history is utilised to construct prediction models for determining creditworthiness and cross selling in the banking industry.

However, a number of FinTechs have created fundamentally new methods for evaluating creditworthiness that use a wider range of data sources. Consequently, the current study's goal was to examine how different data contribute to the assessment of borrowers' creditworthiness. The sample size for the research is 200 respondents (99 government workers and 101 private sector bank employees), who were selected using the quota sampling technique. Most of the primary data used to complete this study was through the administration of questionnaires to respondents to answer a number of questions related to credit eligibility, alternative data, social media-based alternative data and key considerations for psychometric data application. were received. Using SPSS software version 25, correlation and regression tests were used to analyse the data. While analysing the credit eligibility of a bank's clients, the research found that factors of Major Considerations have the maximum impact on Credit Eligibility; however alternative data, social media-based alternative data, and psychometric data play a substantial and beneficial role in determining credit eligibility and fraud detection.

Keywords: Alternate data, Credit eligibility, Fraud, Financial Institutions.

1.INTRODUCTION

Artificial intelligence has several advantages and supports its use in any industry that deals with large amounts of data to ensure accuracy and speed in its services; thus, financial lending services give the most acceptable grounds for its implementation. Today, as the globe moves toward digitalization, the banking industry is not lagging behind. In addition, the covid epidemic revealed to the globe the vast potential and frontiers of digitization and automation. Combining digitization with advancements in data analytics offers immense advantages for businesses in a variety of sectors. Corporations have proved how AI benefits their operations and even business strategies **(McKinsey Global Institute 2018)**. These AI technologies also hold potential for the banking sector. In addition, the relentless rise of data analytics and information base management tools provides the financial industry with a new variety of services and a huge capacity for specialisation and customization of its goods (Carrasco. G.I., 2019).

Recent studies have demonstrated that artificial intelligence is a vital instrument for boosting services as well as the economy as a whole in this day and age of digitalization (Huang & Rust, 2018; Olan et al., 2021).

As such, current advances in artificial intelligence (AI) have made it possible to construct tools for financial specialists that might improve the efficacy and efficiency of corporate operations and performance of the organization,

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particularly in the banking sector. These AI capabilities may have a substantial effect on the financial services industry. As a result, it is projected that AI will not only be effective of completely or partly replacing human resources, but will also be superior to humans. If they want their banks to survive and thrive in today's turbulent economic climate, bank executives must keep a persistent focus on solving challenging issues and capitalising on opportunities. Therefore, it is crucial that managers have access to computerised decision support systems and artificial intelligence software to aid them in making decisions.

Banking industry plays such an important role in the economy that it has captured and captivated the attention and interest of academics, including management science, marketing, finance, and information technology. Currently, banking sector research is an interesting area of study. Today, almost all banking operations and processes are automated as a consequence of advances in information technology. This has resulted in the development of vast quantities of data and new opportunities for artificial intelligence applications.

With a large number of Indians having credit worth millions of Rupees, any innovation that might enhance an organization's earnings on the credit they hold or increase their market share would be quite valuable.As a result, both established institutions and new businesses in the field are always seeking for ways to advance; one such manner that AI may take into account is this.

One of the main functions of bank is lending, which is fundamentally a large data issue, making it a perfect fit for AI and machine learning. There is a correlation between the value of the loan and the creditworthiness of the borrower, and determining this value is a complex operation. The more information a bank knows about an individual borrower (and how similarly situated persons in the past have repaid loans), the more accurately the banking official can judge their viability as a lender. The value of a loan also depends on how much the collateral is worth (car, home, business, artwork, etc.). AI ensures that, in principle, it is capable of analysing all of these data sources concurrently to provide a cohesive judgement without human mistake unlike in traditional banking which relies only on the borrower's credit history and disregards other data. However, today, Certain lenders and financial technology ("fintech") companies attempt to employ alternate data types and more modern methods of data evaluation to evaluate an applicant's creditworthiness. These advances might increase credit accessibility, particularly for those with limited credit histories. However, like with any invention, there may be hazards and unforeseen outcomes. (Kreiswirth.B., 2017). Alternatively, the usage of complicated algorithms may lead to a lack of consumer transparency. This feature of machine learning algorithms may induce scepticism. When machine learning is used to assign credit scores and make credit decisions, it is often more challenging to give customers, auditors, and management with an explanation of a credit score and the associated credit decision. Moreover, others suggest that the use of new alternative data sources, such as internet behaviour or non-traditional financial data, may inject bias into credit decisions (O'Neil, 2017).

Nevertheless, the alternative data has significant promise for identifying reliable borrowers, but their evaluation is almost impossible without the use of AI. Using AI could examine the potential of alternate data to establish the creditworthiness of individuals, especially those without credit histories, to streamline the loan process, and to provide borrowers with a better customer experience. As a result, artificial intelligence has become an indispensable tool, but it also presents certain security and safety risks. Thus, it is crucial to understand how alternative data influences the creditworthiness of bank clients and how they contribute to reducing the likelihood of fraud. Therefore, to fill in this gap our research aims to investigate the role of alternative data in determining credit eligibility and limiting the likelihood of bank fraud.

This study makes two contributions: first, the findings of this research will greatly assist the banking industry in comprehending how Alternative data may be used in the future to facilitate automation with decreasing fraud risks. Secondly, banking authorities may increase client interaction, reduce the operating cost of banking nosiness, improve loan monitoring, enhance the lending process, and reduce errors and delays.

2.LITERATURE REVIEW

According to the research of Russell and Norvig (1995), the knowledge and study of artificial intelligence is the latest on the ancient techniques and ideas of computer science, psychology, semiotics, philosophy and mathematics. These ancient disciplines include psychology, mathematics (which provides us with the principles of logic, deduction and

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induction, probability, decision making and calculation), philosophy (concepts of reason, logic and mind) and semiotics. Zhongzhi (2011) and Russell &Norvig (1995) define The study of replicating and enhancing human intelligence through artificial intelligence use of artificial technology to create intelligent robots. Additionally, they said that AI should be capable of rational action and thought, despite the claims of some that AI should act and think like humans.

2.2 AI for Banking Operation

Credit score example: Credit scoring is not a new concept; in fact, it was one of the early applications of statistical modelling in finance (A. Kankanhalli, Y. Charalabidis, and S. Mellouli, 2019). Banks increasingly use transactional data, statistical analysis, decision trees, and regression to calculate the difference between a consumer's credit risk and capacity to repay a loan in order to more accurately estimate the consumer's credit risk and ability to repay a loan. AI technology increases the precision of credit ratings and the availability of credit by minimising risks and the quantity of both false-positive and false-negative results. This will aid banks in determining the ideal debt repayment strategy for their customers. It also guarantees that banks manage credit risk appropriately, which is vital for financial stability. This is crucial, since there are several Internal Rating-Based (IRB) Approach oversight requirements in this industry (T.M. Harrison , L.F. Luna-Reyes , T.A. Pardo , N. DePaula , M.M. Najafabadi , J.M. Palmer , 2019). These technical criteria are intended to ensure that model outputs and risk-weighted exposures are similar and consistent.

2.3 Credit evaluation and loan/insurance underwriting

The actual help comprises of a plethora of financial organisations aiming to do this. iSentium (2017), for instance, leverages proprietary algorithms to measure consumer sentiment and forecast future economic activity by analysing millions of tweets and social media posts. Investment banks and hedge funds commonly use iSentium.

Douglas Merrill, a former CIO at Google, founded ZestFinance in 2017, which created a machine-learning solution to enable more knowledgeable and effective relationships among borrowers and lenders. Traditional lending practises have not altered over the past 50 years, and they still base their decisions on a small number of data points and are frequently biassed (less than 50). ZESTFinance is developing ZAML (Zest Automated Machine Learning) to detect millions of new borrowers using a wide range of big data sources while simultaneously reducing bias from credit analysis. They contend, based on years of investigation, that there is no one deciding element in credit analysis; thus, ZAML will aid in more correctly selecting good borrowers by analysing hundreds of data points. In addition, it aids in the elimination of bias. As the researchers learned, when a borrower misses a payment and requests an extension, it does not necessarily mean that he or she will always be a bad borrower, and the researchers were surprised to find that various other indicators also indicate missed payments. Are related to the possibility of doing. This is especially important for younger individuals with little or no credit history, a group that traditional underwriters often overlook. ZAML explain ability technologies provide petitioners in adverse action cases with legally required details on how the conclusion was reached, so removing the "black box" of machine learning.

2.3.1 Enhancing credit scores with alternate data

Innovation has centred on aiding lenders to boost their loan approval rates by giving additional data on applicants who lack sufficient conventional data.

UK proptech company CreditLadder has created a platform that enables users to boost their credit scores using their rental payment history, along with Experian and Equifax. The applicant's bank rent payment history is retrieved using TrueLayer's Open Banking API, and this information is then applied to the applicant's overall credit score. (Holmes.C) (2020).

Another U.K. FinTech, Aire, joins If the applicant doesn't have enough supporting documents to prove his or her creditworthiness to the lender, the online loan application process may not be completed. Aire uses a real-time API interface to communicate with lenders. The applicant's current financial situation, spending habits, employment history, and lifestyle are examined by Aerie's machine learning algorithms through a virtual interview to create a behavioral profile that the lender will be able to provide. Provides assistance in deciding whether to accept the money

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or not. Aire has assisted its partners in disbursing around $10 billion in loans by raising acceptance rates while keeping the lender's tolerance for risk.

• Construction of alternative lending profiles

Other entrepreneurs are concentrating on creating a more thorough application profile, which frequently serves as the only criteria used by their partnering lenders to make decisions.

South-East Asian, African, and South American individuals without credit histories can construct credit profiles with the aid of Lenddo, a Singapore-based corporation. Lenddo uses millions of digital footprint data points, such as social network usage, browsing patterns, geolocation, and smartphone data, to determine a person's creditworthiness. Since Lenddo's debut four years ago, has allowed more than 5 million applicants in 15 different countries to obtain loans from its partner lenders.

Users can create an independent credit report using their open banking data with Credit Kudos, a "challenger credit agency" established in the UK. A variety of financial information, including the user's regular banking and payment practises, are included in this report. Biometrics and behavioural analytics will be able to be included into Credit Kudos' credit rating systems as a result of its recent agreement with the artificial intelligence technology company Cybertonica.

Additionally, localised use of traditional credit rating systems may be the most effective. An American FinTech company named Students and employees from eight different nations can create "credit passports" using data from international credit agencies according to Nova Credit. Customers can then apply for credit cards, student loans, and other lending products through the network of partners that Nova Credit has established in the United States (including American Express and IntelliRent) (Holmes, C.) (2020).

• Lending to underbanked borrowers

Some fintech companies use their technology to make loans directly to customers, while most innovators in credit scoring use their algorithms to help other lenders more accurately assess borrowers' creditworthiness.

American company Tala provides micro loans in many countries of the world including Kenya, Mexico, India and Philippines. Due to the lack of traditional data in these countries, lock company credit scoring algorithms are largely based on using the applicant's phone and the internet to assess whether to grant the loan to the applicant and at what interest rate. Have to give loan. For this purpose, similar to Branch, a mobile app-based micro lender, the contact list of applicants' smartphones, GPS information, text and call history, transactions with the Branch platform and customer support interactions are all heavily mined.

Even while atypical lenders and unconventional data are more common in poor countries, credit is far from being available to everyone in industrialised countries. For instance, Deserve provides credit cards to Americans without a social security number or credit history. Instead, deserve looks at a candidate's bank account activities to assess creditworthiness, with consistent earnings (from any source) and timely rent/bill payments serving as the most crucial criterion.

These innovative solutions increase credit availability and affordability for previously underserved groups, whether by enhancing standard credit score data, creating alternative credit profiles, or directly awarding credit. In parallel, alternative credit scoring methods are strengthening algorithms that previously relied on traditional data by enhancing risk modelling for current lenders. These prediction models will probably be used by both traditional and alternative lenders to more accurately assess creditworthiness as machine learning technologies advance through the processing of ever-increasing amounts of data. (Holmes.C (2020)

2.4 A.I. and bank performance

According to Canbas et al., there are at least two major reasons why studying bank failure is so important (2005). First, regulatory bodies can manage and supervise banks more effectively if they have a better understanding of the

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causes of the crisis. Second, by preventing failure or lowering public spending, the capacity to distinguish between competent and distressed institutions may lower the estimated cost of bank collapse.

Although many failure projections have incredibly promising classification accuracies, Gaganis et al. (2006) remark that a reoccurring issue is that they focus on categorising banks into two groups: failed and non-failed. The model's usefulness is reduced by categorising banks as "poor" or "good". It is obvious that the division of the data into many categories relates to a different body of study that focuses on credit risk modelling and aspires to mimic credit agency ratings.

An expert system for sales in banking applications was developed by Collins in 1984. Despite this, numerous research showed that knowledge-based models had little impact on management decision-making.

During the 1990s, data mining improved insurance basic bank operations via the use of intelligent decision models (Anand, Patrick, Hughes & Bell, 1998).

AI has just reduced technical inefficiencies at Indian banks by 11%, and when combined with massive volumes of data, it allows for clever marketing (Kushwaha, Kar&Dwivedi, 2021 ;Mor& Gupta, 2021 ; Verma, Sharma, Deb & Maitra, 2021).While E-popularity banking's has risen in developing countries, the adoption selection problem posed by the range of organisations demands for more study into their use (Gupta, Raychaudhuri&Haldar, 2018).

In developing nations, Western-centric service value scales are only partially adopted (Roy, Paul, Quazi& Nguyen, 2018). By using generalisations, financial services fail to meet their long-term goals and widen the digital divide (Katiyar&Badola, 2018; Lagna&Ravishankar, 2021; Rana, Luthra, & Rao, 2019). For routine cash withdrawals and deposits, automated teller machines (ATMs) have purportedly replaced human tellers, lowering customer interaction (Huang & Rust, 2018).Therefore, for effective banking information management, recognising the activities is crucial. There aren't many empirical studies, and this kind of study is rare (Hasheminejad&Khorrami, 2018 ;Hoehle, Scornavacca& Huff, 2012).

Academics started to incorporate a large variety of transdisciplinary notions as the field expanded. Despite the robustness of global banking, current research indicates that banks have a casual aversion to technology due to expenditures that might result in bankruptcy, closure, or acquisition (Deloitte, 2019). In addition, although banking is increasingly reliant on technology, the frameworks have not been thoroughly established by information systems research (Sundarraj& Wu, 2005).

For improved decision-making, many machine learning models and methods are helpful(González-Carrasco, Jiménez-Márquez, López-Cuadrado, & Ruiz-Mezcua, 2019; Kar&Dwivedi, 2020).

2.5 Machine Learning and Banking

The banking business has used computer resources and infrastructure since the late 1950s, when the age of computer science began. Since then, data processing and storage have become the focal point of every worldwide financial institution. In addition, being at the forefront of digital banking services is increasingly crucial to the success of a bank. Based on the digital services and account security provided by each institution, customers as young as thirteen and as elderly as eighty-five may choose to remain with their present bank or move to a new one. Banks use computer programmes for a variety of internal operations (accounting, human resources, the stock market, etc.), in addition to providing an interface for other banks and government agencies (such as accounting, personnel resources, the stock market, etc.). Despite the fact that these systems could manage vast volumes of data, they lacked the ability to extract insights or reveal hidden patterns in data utilising contemporary computer technology. Despite the fact that a small number of machine learning applications have been in this business for decades, machine learning and artificial intelligence have only recently emerged as a significant influence in the provision of financial services (J. Sharma , G.S. Sindhu , S. Sejwal , J. Solanki , R. Majumdar , 2019). According to J. Li, R. Wang, J. Wang, Y. Li, and Y. Li, the banking industry employs complex methodologies for credit assessment, branch performance, e-banking, client segmentation, and retention (2018). In spite of this, the introduction of Bitcoin and Blockchain technology has spawned new financial firms, needing system modifications to accommodate these new technologies. As the usage of mobile devices expands, new services are being created to accommodate a larger consumer base. These devices

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generate vast quantities of data, which must be analysed to reveal hidden patterns. However, contemporary financial institutions must also address concerns such as money laundering and mortgage fraud, which may be addressed by machine learning and big data technology. In areas such as credit, prediction, fraud, and bankruptcy, banks have made significant machine learning expenditures (J. Li, R. Wang, J. Wang, Y. Li, 2018). The credit score is also essential for banks, since it helps them choose whether to provide loans.

3. RESEARCH METHODOLOGY

The current study is an exploratory cross-sectional, qualitative, and quantitative study. The study is based mostly on original information that was gathered through an empirical investigation. The empirical study was conducted by distributing a questionnaire or schedule for demographic information, important credit eligibility factors, alternative data, alternative data based on social media, and application of psychometric data. Respondents were prompted to answer questions based on a five-point LIKERT scale (Strongly Agree (5), Agree (4), Neutral (3), Disagree (2), and Strongly Disagree (1)) regarding some statements relating to the Major Considerations for Credit Eligibility, Alternative Data, Social Media based Alternative Data, and Psychometric data Application.

The sample size comprises of 200 respondents (99 employees of government and 101 employees of Private sector banks) and these respondents were chosen using Quota Sampling Technique. Further, reliability analysis, normalcy analysis, cross tabulation and correlation & regression analysis were also performed to fulfil the objective of the study.

4. DATA ANALYSIS & INTERPRETATION

4.1 Demographic Profile of the respondents

There were 200 respondents overall, of whom 99 were from Government Bank and 101 were from Private Bank, according to the demographic profile of the respondents. Additionally, it was shown that the majority of responders at both public and private banks were men.

Further, it was revealed that in both bank type i.e. private & public bank, very few respondents were of 21 years to 30 years age group. The respondents were more or less same in categories of 31 years to 40 years age group, 41 years to 50 years age group and 51 years to 60 years age group. Moreover, it was also revealed that majority of respondents in both the types of banks were Middle Level Executive and 2remaining were Senior Level Executive.

4.2 Correlations Analysis: Correlations among Independent Variables (Major Considerations for Credit Eligibility, Alternative Data, Social Media based Alternative Data & Psychometric data Application) and Dependent Variable Overall Consideration for Credit Eligibility

Analysis of correlations has been done to investigate the relationship between Major Considerations for Credit Eligibility, Alternative Data, Social Media based Alternative Data & Psychometric data Application (Independent Variable) and Overall Consideration for Credit Eligibility (dependent variable).

- ***Null hypothesis (H0)-1:*** *There is no significant correlations between* Major Considerations for Credit Eligibility *(Independent Variable) and Overall Consideration for Credit Eligibility.*
- ***Null hypothesis (H0)-2:*** *There is no significant correlations between* Alternative Data *(Independent Variable) and Overall Consideration for Credit Eligibility.*
- ***Null hypothesis (H0)-3:*** *There is no significant correlations between* Social Media based Alternative Data *(Independent Variable) and Overall Consideration for Credit Eligibility.*
- ***Null hypothesis (H0)-4:*** *There is no significant correlations between* Psychometric data Application *(Independent Variable) and Overall Consideration for Credit Eligibility.*

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Table-Correlations Matrix

Correlations						
		Overall Consideration for Credit Eligibility	Major Considerations for Credit Eligibility	Alternative Data	Social Media based Alternative Data	Psychometric data Application
Pearson Correlation	Overall Consideration for Credit Eligibility	1.000	.845	.684	.386	.658
	Major Considerations for Credit Eligibility	.845	1.000	.376	.106	.368
	Alternative Data	.684	.376	1.000	.052	.385
	Social Media based Alternative Data	.386	.106	.052	1.000	.246
	Psychometric data Application	.658	.368	.385	.246	1.000
Sig. (1-tailed)	Overall Consideration for Credit Eligibility	.	.000	.000	.000	.000
	Major Considerations for Credit Eligibility	.000	.	.000	.067	.000
	Alternative Data	.000	.000	.	.231	.000
	Social Media based Alternative Data	.000	.067	.231	.	.000
	Psychometric data Application	.000	.000	.000	.000	.
N	Overall Consideration for Credit Eligibility	200	200	200	200	200
	Major Considerations for Credit Eligibility	200	200	200	200	200
	Alternative Data	200	200	200	200	200
	Social Media based Alternative Data	200	200	200	200	200
	Psychometric data Application	200	200	200	200	200

Interpretation

- **Major Considerations for Credit Eligibility:**Major Considerations for Credit Eligibility (Independent Variable) and Overall Consideration for Credit Eligibility have a positive association (.845), according to the correlation matrix shown above (dependent variable). According to the correlation analysis, the two variables are significant at a level of 0.000, which is lower than the study's 0.05 level of confidence. The findings show a significant and favorable correlation **hence, it can be concluded that the Null Hypothesis is rejected.**

- **Alternative Data:** The correlation matrix shown here demonstrates that Alternative Data (Independent Variable) and Overall Consideration for Credit Eligibility have a positive correlation (..684). (dependent variable). According to the correlation analysis, the two variables are significant at a level of 0.000, which is lower than the study's 0.05 level of confidence. The findings show a substantial and favorable association**hence, it can be concluded that the Null Hypothesis is rejected.**
- **Social Media based Alternative Data:**According to the correlation matrix shown above, the overall consideration for credit eligibility and Social Media-based Alternative Data (Independent Variable) have a positive association (.386). (Dependent variable). According to the correlation analysis, the two variables are significant at a level of 0.000, which is lower than the study's 0.05 level of confidence. The findings show a substantial and favorable association **hence, it can be concluded that the Null Hypothesis is rejected.**
- **Psychometric data Application:**The correlation matrix shown above demonstrates that the overall consideration for credit eligibility and the application of psychometric data have a positive association (.658). (Dependent variable). According to the correlation analysis, the two variables are significant at a level of 0.000, which is lower than the study's 0.05 level of confidence. The findings show a substantial and favourable association **hence, it can be concluded that the Null Hypothesis is rejected.**

4.3 Regression Analysis: Impact of Major Considerations for Credit Eligibility, Alternative Data, Social Media based Alternative Data & Psychometric data Application on Overall Consideration for Credit Eligibility (dependent variable)

- *Alternate Hypothesis-1 (H1): There is positive and significant Impact of* **Major Considerations for Credit Eligibility** *(Independent Variable) on* Overall Consideration for Credit Eligibility (dependent variable).
- *Null Hypothesis-1 (H0): There is no positive and significant Impact of* **Major Considerations for Credit Eligibility** *(Independent Variable) on* Overall Consideration for Credit Eligibility (dependent variable).
- *Alternate Hypothesis-2 (H1): There is positive and significant Impact of* **Alternative Data** *(Independent Variable) on* Overall Consideration for Credit Eligibility (dependent variable).
- *Null Hypothesis-2 (H0): There is no positive and significant of* **Alternative Data** *(Independent Variable) on* Overall Consideration for Credit Eligibility (dependent variable).
- *Alternate Hypothesis-3 (H1): There is positive and significant Impact of* **Social Media based Alternative Data** *(Independent Variable) on* Overall Consideration for Credit Eligibility (dependent variable).
- *Null Hypothesis-3 (H0): There is no positive and significant Impact of* **Social Media based Alternative Data** *(Independent Variable) on* Overall Consideration for Credit Eligibility (dependent variable).
- *Alternate Hypothesis-4 (H1): There is positive and significant Impact of* **Psychometric data Application** *(Independent Variable) on* Overall Consideration for Credit Eligibility (dependent variable). \
- *Null Hypothesis-4 (H0): There is no positive and significant Impact of* **Psychometric data Application** *(Independent Variable) on* Overall Consideration for Credit Eligibility (dependent variable).

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The objective is to measure the relationship and Impact of Major Considerations for Credit Eligibility, Alternative Data, Social Media based Alternative Data & Psychometric data Application on Overall Consideration for Credit Eligibility (dependent variable)

Multiple correlation coefficient (R) values range from 0 to 1. The value of the multiple correlation coefficients (R) indicates how well the regression equation fits the data. It demonstrates a strong correlation between the dependent and independent variables. **SQUARE R:** The amount of variance in the dependent variable that is explained by the independent variables is expressed by the square of the multiple correlation coefficient, also known as the **coefficient of multiple determination (R2).**

Table-4.99 –: Regression: Model Summary

Model Summary									
					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	1.000[a]	1.000	1.000	.00000042	1.000	36591746972385232.000	4	195	.000
a. Predictors: (Constant), Psychometric data Application, Social Media based Alternative Data, Major Considerations for Credit Eligibility , Alternative Data									

R-measurement SQUARE's of the **model's** explained variance showed that **(R2=1.000)**, which means that about **100% of the variance** in independent variables was explained. - Important Factors Affecting Credit Eligibility, Alternative Data, Social Media based Alternative Data & Psychometric data Application and Overall Consideration for Credit Eligibility (dependent variable).

Table-Coefficients

Coefficients[a]											
		Unstandardized Coefficients		Standardized Coefficients			Correlations			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	5.771E-17	.000		.000	1.000					
	Major Considerations for Credit Eligibility	1.000	.000	.597	201905019.484	.000	.845	1.000	.533	.799	1.251
	Alternative Data	1.000	.000	.353	118640586.269	.000	.684	1.000	.313	.786	1.273
	Social Media based Alternative Data	1.000	.000	.245	89807131.314	.000	.386	1.000	.237	.937	1.068
	Psychometric data Application	1.000	.000	.242	79568245.968	.000	.658	1.000	.210	.752	1.330
a. Dependent Variable: Overall Consideration for Credit Eligibility											

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Interpretation:

- **Major Considerations for Credit Eligibility-**As can be seen, the value of the standardised (eta) coefficient for the independent variable Major Considerations for Credit Eligibility is 0.597, which means that a 1-unit positive standard deviation change in it would increase the dependent variable "Overall Consideration for Credit Eligibility" by 0.597 units. Therefore, it can be inferred that Major Considerations for Credit Eligibility have a positive and significant association with the dependent variable because the value of the coefficient is significant. Therefore, we can conclude that the Null Hypothesis (H0) is rejected and the Alternative Hypothesis (H1) is accepted.
- **Alternative Data-**As can be observed, the standardised (eta) coefficient for **Alternative Data** (Independent Variable) is 0.353, which suggests that a 1-unit increase in its value would increase the dependent variable "Overall Consideration for Credit Eligibility" by 0.353 units. Therefore, it may be stated that Alternative Data have a positive and significant relationship with the dependent variable because the value of the coefficient is significant. Therefore, we can conclude that the Null Hypothesis (H0) is rejected and the Alternative Hypothesis (H1) is accepted.
- **Social Media based Alternative Data-**As can be observed, the standardized (eta) coefficient for the Social Media-based Alternative Data (Independent Variable) is 0.245, which suggests that a 1-unit positive standard deviation change in it would raise the dependent variable's "Overall Consideration for Credit Eligibility" by 0.245 units. Therefore, it can be argued that Social Media-based Alternative Data have a positive and significant association with the dependent variable because the value of the coefficient is significant. Therefore, we can conclude that the Null Hypothesis (H0) is rejected and the Alternative Hypothesis (H1) is accepted.
- **Psychometric data Application-**As can be observed, the standardized (eta) coefficient for Psychometric Data Application (Independent Variable) is 0.242, which suggests that a 1-unit positive standard deviation change will increase the dependent variable "Overall Consideration for Credit Eligibility" by 0.242 units. Therefore, it may be argued that, because the coefficient's value is significant, the link between the dependent variable and the psychometric data application is both positive and significant. Therefore, we can conclude that the Null Hypothesis (H0) is rejected and the Alternative Hypothesis (H1) is accepted.

5. CONCLUSION & SUGGESTIONS

Alternative data in banking sector is that big data which gives insight into the credit worthiness of a customer. It is a unique way of assessing the credit eligibility of the customers by capturing the wide information available. As suchthe present study was designed to understand the role of alternative data in ascertaining credit eligibility of the customers in banks. Thus, the results showed some interesting findings that while analysing the credit eligibility of the customers in a bank, major considerations for credit eligibility, alternative data, social media based alternative data & psychometric data application based data all have significant and positive role in determiningg the credit eligibility.

The major considerations for assessing credit eligibility like age occupation, residence, type of family, number of dependents, earning members in the family, total yearly income of the family, ownership status of house (Owned/Rented), previous history of loan from other banks, amount of loan received previously, default status, minimum, net monthly income, credit score (CIBIL Score), collaterals/guarantee, relationship with guarantor, guarantor's documents, assets owned, value of the property/assets owned and credit card are all very essential and holds a prime role in determining a person`s paying capacity. As such, the study revealed highest correlation between it with overall consideration for credit eligibility.

The next independent variable being alternative data itself also showed positive & significant relationship with overall consideration for credit eligibility in banks. This result seemed very obvious as by keeping a check on a borrower`s saving pattern, his work experience & gold ornaments with the borrower, it can be gauged that whether he/she will be able to repay the loan amount and interest on time or not. Apart from this, the mobile nos. of blood relatives of borrower can also be used to fetch information and contact them whenever required. It gives a kind of transparency that when required the bank can call and contact the borrower or their close ones. The electricity bill/gas bill/house tax/ water tax, other online paid bills etc. also let the bankers peep into the economic status of the person applying for loan.

Moreover, the e-buying activities that have become a part of our daily life has also been a good tracker of our record at the banks in deciding the credit worthiness. Information like E-commerce transaction frequency & amount, amount spend on shopping, score/points from shopping, amount in the E-wallets amount & Frequency of transaction and also food delivery services frequency & amount points to the financial health of a person and banking officials use it under the broad term of big data analytics using alternative data.

The next metric used as an alternative data to determine the credit eligibility of the borrower is the Social Media based Alternative Data. Social media today is not just a connecting link to our friends and others but have widen its scope and horizons to become a platform for multiple tasks. One such task as used in banking business is to extract information relevant to them for ensuring healthy outflow of credit to the eligible borrowers. As such, the total count of friends & followers on facebook/instagram/twitter and other social media platforms, posts depicting places visited and hotels visited, types of apps used & social media groups all give one hint or the other of how eligible a borrower is and how worthy is he/she is of the loan.

Lastly, another interesting aspect of a borrower through Psychometric data Application was used as an assessment tool of the borrower`s credit worthiness. Fascinatingly, a borrower`s intelligence, honesty, character certificate, health condition & health insurance also significantly impact the credit worthiness of the person.

SUGGESTIONS-

- Information extracted from social media and other apps must be thoroughly verified to minimise the chances of bad debts.
- The data collected from social media needs to have enough pertinent details about the consumer in order to provide them with an alternative credit score
- Alternative credit variables could be more challenging to explain to credit applicants. Therefore, efforts should be made to set up proper dialogue and effecti9ve communication system between the parties involved.
- Alternative data cannot be considered as fully reliable and sufficient in alone unless it is combined with the traditional data.
- Proper mechanism for implementation and regulation of alternative data should be made.

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