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Analysis on Use of- Alternate Data factors as a Tool for Predicting Loan Delinquencies and reducing Loan defaults in an Indian NBFC

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Abstract:

One of the biggest challenges faced by NBFC across the country from years is the challenge of Default and delinquencies. Alternate data has evolved as a method to overcome the issue. The current paper tries to identify many alternate data variables identified across literature, further based on the opinion of more than 300 credit managers of the selected NBFC branches across the country, has identified factors from the same. The researcher further has taken the opinion of these NBFC credit managers as to the new rating systems based on the factors identified have been able to predict the loan delinquencies in time and have been able to reduce the loan defaults. The analysis leads to a favourable conclusion.

Keywords: Alternate Data, Alternate Data Factors, Loan Delinquencies, Loan Default

1. INTRODUCTION

The Financial Service sector of our country comprises of mainly capital markets, insurance sector and non-banking financial companies (NBFCs). But post subprime crisis, the status of NBFC‟s has changed remarkably in terms of Regulatory reforms, technology used and

Even the status in the financial system has diverse. Many challenges have come across and one of them is, it faces the problem of loan delinquencies and defaults. Mainly the NBFC‟s in the country have their business offices set in rural areas due to the business opportunities in those areas. Hence, variety of traditional methods that the banking and Non banking sector uses for the Loan assessment, but post disbursement, there are very limited methods for prediction of Loan default.

Delinquencies: "Delinquent describes something or someone who fails to accomplish that which is required by law, duty, or contractual agreement, such as the failure to make a required payment or perform a particular action."(investopedia)

Loan Delinquency: Based on the definition of Delinquency, it can be said that a loan delinquency occurs when an individual or corporation with a contractual obligation to make payments against a debt, a loan payments, does not make those payments on time or in a regular, timely manner.

Delinquent vs. Default

"In a financial sense, delinquency occurs as soon as a borrower misses a payment on a loan. In contrast, default occurs when a borrower fails to repay the loan as specified in the original contract. Most creditors allow a loan to remain delinquent for some time before considering it in default. The duration lenders allow for delinquency depends on the creditor and the type of loan involved."*(investopedia)*

Status of NBFC's in India: Since evolution, NBFC"s in India has expanded rapidly, in terms of size, diversity in operations, services provided and role in bringing inclusive growth. The sector has been growing shoulder to shoulder with Private banks with tech innovations and adaptations in operations of business and also in credit rating, credit evaluation and in fact has been a step ahead in terms of modern banking solutions.

Challenges in Front of NBFC's

Though, the NBFC sector has seen a tremendous growth in a short term, but its facing a lot of challenges right from incorporation to becoming operational. All these challenges are in the process of being resolved step by step by the Regulatory authorities with the dynamic reforms.

But the major challenges faced by Indian Financial Sector i.e. banking sector are faced by the NBFC"s also. The banking sector in India has been facing a problem of Loan delinquencies and defaults since ages. Even the NBFC"s are facing the same problem. The researcher has tried to explore the details about the same in the following segments.(Live mint article Indian banks are in for a 20 trillion hole)

Diagram no. 1– Challenges faced by NBFC's

Source: https://corpbiz.io/learning/challenges-encountered-by-nbfcs-their-remedies/

The 90+ Days Past Due percentagesof Balance Level Delinquencies is highest for

NBFC‟s among the Three, i.e. Private Banks, Public sector banks and NBFC‟s. The percentage has gone up from 4.59% in August 2019 to 5.04% in August 2020.(Economic times article „NBFC‟s gross npa ratio rises to 6.3 pc in Sept- RBI report‟)As per the report of RBI further, In September 2019 the gross NPA‟s of NBFC‟s in India_increased to 6.3 percent which was earlier 6.1 per cent in March 2019.(Industry Insight report –CIBIL, 2019)

The quarter three, overall delinquency rates which we can see for the year 2019, above is 51 bps high than that of overall Delinquency rate a year ago. The Delinquency rates for public sector (PSU) and private sector (PVT) banks for the period of comparison reduced in that period by 26 bps and 9 bps respectively. (Crisil NBFC report 2020)

In modern times, the lender has given rise to many new methods that can help in predicting the Loan defaults, Alternate data factors is one such factor. The current study tries to understand the use of alternate data by creating a strategic model for prediction of loan delinquencies and possible reduction in Loan defaults of one such deposit taking NBFC, **'Mahindra & Mahindra Financial Services'**.

Alternative Data: "Alternative data refers to data used by investors to evaluate a company or investment that is not within their traditional data sources (financial statements, SEC filings, management presentations, press releases, etc.). It helps investors get more accurate or more granular insights and metrics into company performance than traditional data sources."(alternativedata.org)

1.7 Use of Alternate data for Loan Delinquency prediction:

In spite of careful lending practices followed by banks & financial Institutions, the trend of Rural loan defaults continue to grow and the finance companies either reject the loan applications based on scoring pattern or lend at higher rates to cover the additional risk. Rural economy mostly relies on environmental criteria‟s and impact to these affects the entire community. Thus, any prediction made at the time of lending money is not correct for the entire tenure of the loan. Earlier researchers had brought out brilliant information and ideas on the current trends on account of evaluation from fintech solutions.

With the evolution of Fintech and mobile/smart phone penetration in India (which is expected to rise to 730.7 million which is above 54% of India‟s population) Data that gets generated in the customer mobile phones will be a great help to understand the changes that happens to customer business performance, environment and behaviour. To enable this, the customer mobile application of these rural finance companies should be activated with features, to capture the relevant data from the SMS, Call, Social chats, etc that happen from the mobile phone. Such data is called „*Alternate Data*‟. The customer should be encouraged to use the mobile application of the NBFC‟s.

Further, information about the local incident, such as new projects, strikes, flood, drought, communicable infections, etc., are also available freely in various authenticated websites of the State/Central

Government and news agencies. *This information also can be classified as 'Alternate Data'*.

Diagram No.2

Source:https://www2.deloitte.com/us/en/pages/financial-services/articles/infocus-adopting-alternative-data-investing.h

Alternate Data if collected can surely help the lenders to predict the loan delinquencies. The resultant process can be seen in the diagram above.

Thus the researcher has done a thorough review of literature in the specified area.

2. REVIEW OF LITERATURE:

The researcher has explored a wide range of literature available in the subject area to understand the Concept of Alternate data in detail, and To understand the uses of the same to study the usable factors for the selected study. The review of papers published in various reviewed international journal is presented below.

Alternative data

"A wide array of data falls outside the traditional credit data definition that can be deployed throughout the loan life cycle. Data sources that fall outside of that scope are generally referred to as "alternative,"". (Viani B. Djeundje 2021).

"Alternative data is, put simply, any information that is non-market data. As such any usable information or data that is not from a financial statement but can be used in obtaining insight within the investment process." (Ramkumar Srinivasan 2019)

There is a huge amount of data that falls under Alternate Data. Majority of it being the payment bills related to rent, cell phones, etc. Normally these factors are not included in traditional credit report. Besides, new loans taken their repayment history bank account transactions are also the data sources. With wide usage of Phones and apps for financial transaction and increased use of internet banking these transactions are carried frequently.

On the basis of the Credit scores and predicting the Loan default it can help the financial institutions a lot to prevail the Credit Risk. In addition the data used in traditional models i.e. educational background, occupation and other demographics along with the alternate data like Social Media activity and online activities can be of lot of use for various functions including marketing of products, fraud detection, rejection of loans and designing collection strategies. (Viani B. Djeundje 2021).

Agarwal S (2019) has taken the study related to the Alternate Data to the new level where they try to examine the possibilities of using an individual"s online behavior captured from their mobile phones for predicting the possibility of default. There are few pionner studies in the field of, use of machine learning (Chava, Paradkar & Zhang (2017), Use of Fintech for credit scoring using digital data Berg, Burg, Gombovi´c & Puri (2019), A combination of Fintech and savings mechanism in D"Acunto, Rauter, Scheuch &Weber (2019) and use of Robotics in Finances in D"Acunto, Prabhala & Rossi (2019) and Fuster,(2018). All the studies are based on the use of Mobile and digital data and using it for various uses in the field of finances.

Further Viani B. Djeundje (2021) in their study attempt "to evaluate the predictive accuracy of models using alternative data that may be used instead of credit history, to predict the credit risk of a new account." The researchers have proved that use of email data, Psychometric variables and Demographic variables together can give more accurate prediction of possible loan defaults than conventional data.

Agarwal S. (2019) in their study, have tried to analyze if unstructured mobile footprint data of the customer can replace the traditional data for credit scoring. And it found that the mobile footprint has outperformed the credit score prediction of loan approvals and prediction of defaults. The data includes "Deep Social Footprint data" based on call logs which is used for prediction based on machine learning.

The experiments of using unconventional data have started since late 2000s by various researchers like De Cnudde and Oskarsdottr. The researchers have tried to check the predictive accuracy only using the unconventional data with conventional data. And found that the unconventional variables have discriminatory power of classifying good and poor re-payers. Further adding to it, Agarwal (2019) suggests psychometric data in to it a combination of psychometric data and characteristics of email usage collectively give a better accuracy in prediction. And they add, "Our work suggests that since these types of variables increase predictive accuracy, it may be possible for lenders that have large amounts of conventional repayment data to have even more accurate models by using these variables than omitting them which is currently the case."

Challenges in Using Alternative Data

The alternate data along with a combination of analytics can do wonders for financial sector but the other side of coin of the Ramkumar Srinivasan (2019) records the challenges in using data Alternative data then. The other challenges listed are

- Data Availability

- Quality and Consistency
- Objectivity – Data Contextualization
- Technology Complexity
- Prudent Implementation of Big Data Strategies
- Poor systems integration
- Ethics
- Periodic review of Models and Strategies

Alternate data importance

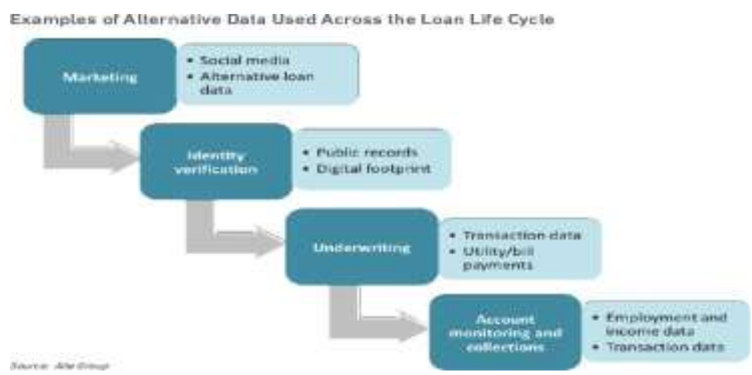
"A wide array of data falls outside the traditional credit data definition that can be deployed throughout the loan life cycle. This data may allow a lender to get a more detailed picture of a consumer‟s financial behaviour and a more accurate picture of the consumer‟s identity and preferences." (Leslie Parish 2018) The researcher tries to

The challenges don‟t reduce the importance of Alternate Data by any means. The paper by Philip Higson(2017)identifies various alternate data factors as tool sets like location data, online shopping data, payment processing data, consumers internet browsing ,job platforms and the companies in which these factors are used. The paper talks about the importance and increasing use of Alt data.

Alternate Data factors

identify the alternate data factors, form the review of literature, with the objective of building a credit scoring based on various alternate data factors collected from the mobile use of the loan Customer. From the study of paper by (Leslie Parish 2018) has identified few important factors along with few mentioned already by other researchers and are mentioned above.

Diagram No. 3 alternate Data Factors and sources across loan life Cycle



Source: (Leslie Parish 2018)

The researcher has specified the alternate data factor and challenges in it. The biggest challenge faced is the availability of data and willingness to share the data for scoring.

Using alternate data for reducing delinquencies

The researcher further has tried to review the literature specifically in the area of Predicting and reducing loan delinquencies using alternate data. A discussion paper by

Julia S. Cheney, „Alternative Data and Its Use in Credit Scoring Thin- and No-File Consumers‟, studies "the continued evolution of supply and demand for alternative data in the credit information markets‟ and concludes "While obstacles remain in moving toward incorporating alterative data into lending decisions by traditional financial institutions, there also seem to be real social and economic incentives for doing so."

The paper gives a detailed discussion on Alt data, factor to reduce the delinquency rates.

3. RESEARCH METHODOLOGY

The researcher here has collected data from more than 300 branches of the selected NBFC i.e. Mahindra & Mahindra Financial Services, spread across the rural areas across the country. The data has been collected from the credit managers of these branches through convenient random sampling method.

The hypothesis is formed and statistically tested. But before that the researcher has identified specific alternate data factors which can be used for prediction.

4. DATA ANALYSIS

Alternate Data Factors:

The researcher further from literature with senior management analysed many alternate data factors and has asked the opinion of credit managers for the timely information of w the given factors that will be helpful in predicting the conversion of a good loan in to a possible default loan. The respondents were not given an idea about the factors being alternate factors. The data collected about the ranks of which all factors from the given list are important to help predict the possible default loan in time is collected and presented below.

Table No.1 Ranking of Alternate data factors

Sr. No.	Particular	NA/0	Rank					Total
			1	2	3	4	5	
1	Location related information	50	36	40	97	53	42	318
2	Local geographical difficulties	19	30	23	83	75	88	318
3	Local communal disturbances	21	22	41	77	86	71	318
4	Local strengths / plus points	22	35	37	84	102	38	318
5	Climatic changes	24	28	25	102	52	87	318
6	Farming failures	14	17	46	89	88	64	318
7	Farming successes	16	17	17	74	91	103	318
8	Business failures	29	21	40	59	87	82	318
9	Business Successes	24	9	36	68	65	116	318
10	Utility Bills Info	30	28	29	74	86	71	318
11	Phone bills info	49	56	46	81	55	31	318
12	New Loan related info	48	61	74	63	45	27	318
13	Financial transactions	22	22	29	65	87	93	318
14	Online Shopping info	19	14	23	79	76	105	316
15	Health info	47	77	55	87	33	19	318
16	Web search info	28	27	38	73	84	68	318
17	Premium dues info	50	66	55	82	40	25	318
18	Loan from others	39	18	46	97	53	65	318

Table No 2 Mean score of Ranks of Alternate data factors

Sr. No.	Factors	Mean Rank
1	Location related information	2.61
2	Local geographical difficulties	3.35
3	Local communal disturbances	3.25
4	Local strengths / plus points	3.02
5	Climatic changes	3.23
6	Farming failures	3.30
7	Farming successes	3.62
8	Business failures	3.26
9	Business Successes	3.54
10	Utility Bills Info	3.17
11	Phone bills info	2.41
12	New Loan related info	2.24
13	Financial transactions	3.42
14	Online Shopping info	3.56
15	Health info	2.12
16	Web search info	3.14
17	Premium dues info	2.22
18	Loan from others	2.95

The data in table no. 1 suggests that Business Success is ranked highest by majority that is 116 respondents out of 318, followed by online shopping information with 105 respondents ranking it highest. Farming Success is the third factor ranked highest with 103 respondents ranking it as most important and useful factor for predicting loan delinquencies. Health information, Premium dues and new loan related info are the factors that are rated as most important by very few respondent managers. To have a better understanding, the researcher further has used the Mean Rank analysis to find out the best ranked factors. The Mean rank analysis is presented above in table no.2

The Mean rank analysis of ranked data of alternate data factors suggests that, Farming successes, Online Shopping info and Business Successes are the top three most important factors for predicting Rural loan Delinquencies with Mean Rank scores of 3.62, 3.56 and 3.54. These factors are followed by, Financial transactions (3.42), Local geographical difficulties (3.35), Farming failures (3.30), Business failures (3.26), Local communal disturbances (3.25), Climatic changes (3.23), Utility Bills Info (3.17), Web search info (3.14), Local strengths / plus points (3.02), Loan from others (2.95), Location related information (2.61), Phone bills info (2.41), New Loan related info (2.24), Premium dues info (2.22) and the least ranked Health info (2.12).As can be seen from the above analysis, though the data gives us the most ranked factors in sequence but the mean ranks are too close. For the better analysis the researcher further has used Factor analysis on the Factor ranks. Which is presented in the below in Table No. 3

Table No 3Factor Analysis - Alternate data factors

Rotated Factor Loadings and Communalities

Varimax Rotation

Variable	Factor1	Factor2	Factor3	Factor4	Communality
Location related information	0.183	-0.304	-0.545	0.221	0.473
Local geographical difficulties	0.074	-0.08	-0.846	-0.068	0.731
Local communal disturbances	0.304	-0.242	-0.559	0.08	0.47
Local strengths / plus points	0.21	-0.339	-0.476	0.176	0.416
Climatic changes	0.025	-0.204	-0.479	0.116	0.285
Farming failures	0.053	-0.246	-0.575	0.288	0.477
Farming successes	0.203	-0.258	-0.258	0.849	0.894
Business failures	0.121	-0.56	-0.28	0.154	0.431
Business Successes	0.327	-0.485	-0.237	0.448	0.598
Utility Bills Info	0.86	-0.153	-0.137	0.144	0.803
Phone bills info	0.866	-0.191	-0.046	0.127	0.804
New Loan related info	0.311	-0.642	-0.304	0.092	0.611
Financial transactions	0.171	-0.567	-0.298	0.241	0.497
Online Shopping info	0.759	-0.071	-0.207	0.142	0.644
Health info	0.412	-0.356	-0.374	0.176	0.467
Web search info	0.765	-0.239	-0.18	0.07	0.68
Premium dues info	0.419	-0.653	-0.088	-0.006	0.61
Loan from others	0.116	-0.75	-0.306	0.161	0.696
Other:	0.594	-0.203	-0.041	0.003	0.395
Variance	3.8306	3.004	2.8323	1.3168	10.9836
% Var	0.202	0.158	0.149	0.069	0.578

The analysis of alternate data factors using Factor analysis help us categorize the variables in 4 factors. As can be seen clearly in the above table factor 1 comprises of all the **'Life and Lifestyle Expenses'** of Borrowers, which includes variables like Utility Bills Information, Phone Bill , Online Shopping ,Health expenses , web search and Premium dues information with highest loading factors. Based on the factor loadings, factor no. 2 comprises of all **'Debt Transactions'** which include new debts, Financial Transactions, and Loan from Others. These variables seem to have a negative relationship with other factors. It simply means of the debt Burden increase, life expenses decreases.

Factor No. 3 is more related with „**Geographical information'** which includes variables like Local geographical & communal disturbances, Local strengths, Climatic changes and Farming failures. These variables form a negative relation with other variables.

Factor No. 4 based on the loading factors can be said to be **'Business Cycles'** which includes variables like Farming and Business Success. The factor has a strong positive loading.

The researcher after identifying the Alternate Data factors based on the opinion of the Credit Managers, has tried to identify if the Alternate Data factors has a significant relationship with Prediction of Delinquencies in time and the timely changes in collection strategy based on the *data derived and ranking based on Alternate Data can reduce the loan defaults. The researcher has formed the Hypothesis accordingly and tested them.*

Hypothesis 01

The alternate data factors have significant relationship with prediction of the loan delinquencies in time.

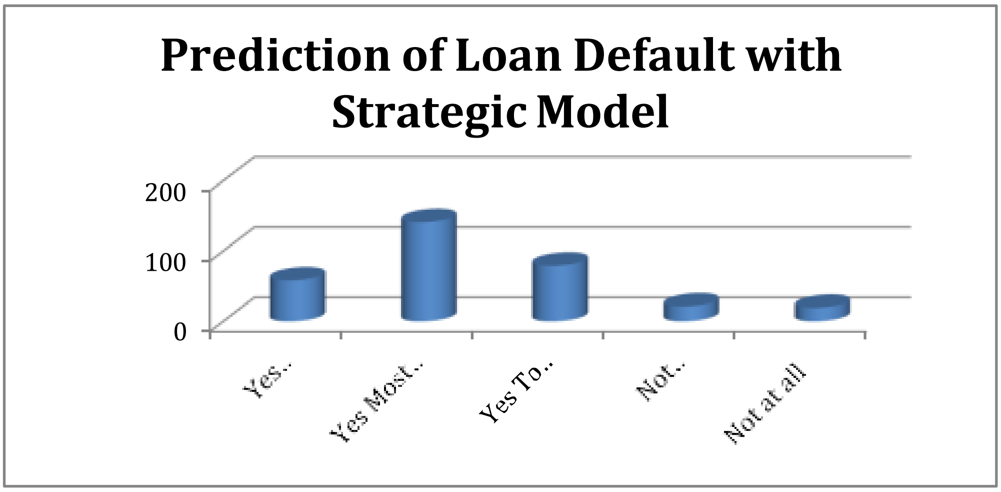
Prediction of Possible Rural Loan Default in time with Strategic Model: The researcher, for the purpose of testing this hypothesis has tried to understand the opinion of respondent credit managers on the usefulness of the Strategic model in predicting the possible Loan defaults in time. The data is analyzed using percentage method. The data collected is presented in table no. 4 and Graph no 1.

Table No 4

Prediction of Possible Rural Loan Default in time with Strategic Model

Sr. No.	Particular	No. of Respondents	%
1	Yes Completely	58	18%
2	Yes Most of it	141	44%
3	Yes To some extent	79	25%
4	Not really, To a very less extent	21	7%
5	Not at all	19	6%
	Total	**318**	**100%**

Graph No 1



The analysis of the above data suggests that majority of the respondent credit managers i.e. 141 respondents out of 318(44%) are of the opinion that with the help of Strategic Model based on Alternate data factors, Most of the Possible loan defaults can be predicted. 58 respondents (18% respondents) feel that they can predict the possible Rural loan default completely with the help of a strategic model of Alt data factors.

So it can be said that 62% of the respondents feel that the strategic model will be useful in prediction, 25% additional respondents feel that the use will be to certain extent only. Only 7% respondent Managers feel that the use will to a very limited extent and 6% respondent Managers feel that the Model .will not be of any use in Predicting possible Loan defaults.

Overall it can be said that majority of the respondent managers feel that the Strategic model based on Alternate Data shall be useful in predicting the possible Rural Loan defaults. Thus it can be said that the Hypothesis that „**The alternate data factors have significant relationship with prediction of the loan delinquencies in time' is accepted.**

Hypothesis 02

Timely changes on collection strategy based on alternate data factors can reduce the delinquencies of rural loan customers.

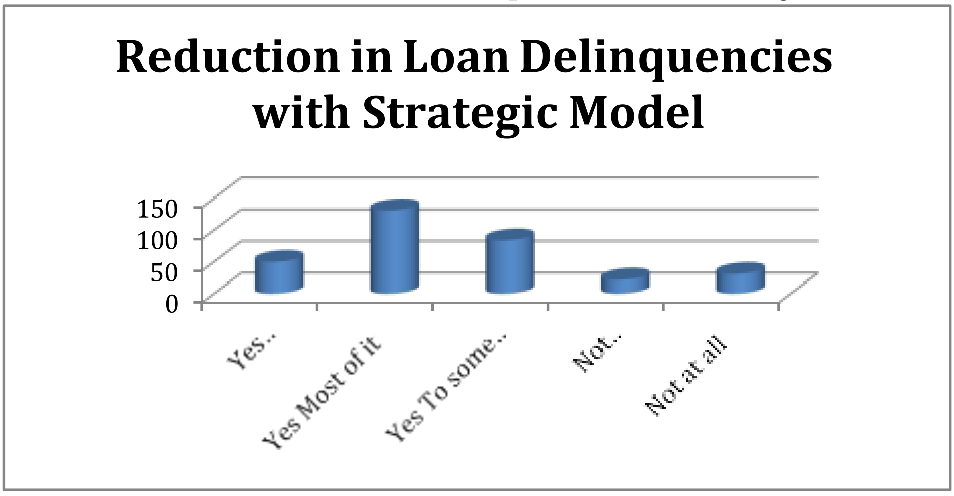
Reduction in Rural Loan Delinquencies with Strategic Model with Timely changes in Collection Policy: The major use after prediction of Possible Loan delinquency in time shall be reduction in rural loan delinquencies. The researcher after understanding the view of the credit managers about the use of Strategic Model in predicting the Loan defaults has tried to collect the data related to opinion of Credit Managers on Reduction on Loan Delinquencies. Researcher has used percentage analysis to test the hypothesis on the data. The Data collected and analyzed is presented in table no. 5 and Graph no 2.

Table No 5.Reduction in Rural Loan Delinquencies with Strategic Model with Timely changes in Collection Policy

Sr. No.	Particular	No. of Respondents	%
1	Yes Completely	50	16%
2	Yes Most of it	131	41%
3	Yes To some extent	84	26%
4	Not really, To a very less extent	22	7%
5	Not at all	31	10%
	Total	**318**	100%

Graph No 2

Possible Reduction in Loan Delinquencies with Strategic Model



The data presented above clearly suggests that, in total 16% (50 out of 318) of the respondents feel that they can reduce the loan delinquencies by changing the collection policy with the use of strategic Model based on Alternate data and 41%

(131 out of 318) respondent Managers feel that they can reduce the Loan delinquencies with the help of a Model. Thus 57% of the respondents are of the opinions that, by changing the collection policy in time reduce the loan delinquencies to a large extent with the help of Strategic Model based on Alternate Data. In addition 26% more respondents feel that the Model may help reduction to some extent . So overall 83% respondent Credit Managers are of the positive opinion about the Model shall be useful. Only 7% respondents feel that the Model will be of a limited use and 10% respondents feel that the timely changes in collection policy with the help of a Model will not be of any use in reduction of rural loan Delinquencies. Thus as per the overall opinion of Credit Managers, it can be said that „**Timely changes on collection strategy based on alternate data factors can reduce the delinquencies of rural loan customers' is accepted.**

5. CONCLUSION

Loan delinquencies and Loan default has been the age old problem be it Indian banking sector or Non Banking Financial Companies in India. The traditional methods have been used to assess the credit worthiness of the loan applicant. But once the loan has been disbursed, the traditional methods further are not really useful in projecting the loan delinquencies and defaults. The modern methods like alternate data have evolved as a blessing to the Non-Banking sector to predict the loan delinquencies in time and reduce the loan defaults. The methods like Alternate Data which are based on the consumption or spending data, life style data, medical expenses and based on Mobile surfing have a significant relationship with predicting timely loan delinquencies and further reduce the loan defaults by changing the collection strategy by using the alternate factors as a timely alert.

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