A study on Artificial Intelligence and Machine Learning in Banking Sector with special reference to term loan

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Abstract

Digital lending platforms are becoming popular day by day. They believe that CIBIL and other credit checks do not paint a complete picture of a loan applicant's credit worthiness. They've taken on to add hundreds and thousands of other data points to their process, not all of which are necessarily related to financial interactions. This can include information such as your educational merits and certifications, employment history, and even trivial information such as when you go to sleep, which websites you browse to, your messaging habits and daily location patterns. This paper explains effective utilization of Artificial Intelligence and Machine Learning. The objectives of the research are to understand the financial contribution of quick loan to the revenue generation, to find out obstacles perceived and current causes that constitutes long process of loan disbursement, to find out changeover demand a prerequisite AI tool for its effective implementation and know what is the impact of the Quick loan on the customers and on economy. An in-depth analysis is done through structured questionnaire asked to bankers and loan customers. The analysis is done and statistical test is applied on effect of quick and safe loaning (lending of banks) by using Artificial Intelligence on the effectiveness of repayment and collection of loan (reduce in Non-Performing Assets); in the context of utility; and in the context to dependence on other disbursement tools of loaning.

Keywords: Digital lending, quick loan, Artificial intelligence, Machine Learning and CIBIL.

Introduction:

As digital lending continues to grow in size, companies are looking for ways to make their services more efficient and profitable to both lenders and borrowers. And they believe artificial intelligence and big data hold the key to the future of loans. Lenders traditionally make decisions based on a loan applicant's credit score, a three-digit number obtained from credit bureaus such as CIBIL, Experian and Equifax. Credit scores are calculated from data such as payment history, credit history length and credit line amounts. They're used to determine how likely applicants are to repay their debts and to calculate the interest rate of loans. If you have a low credit score, you're considered a risky borrower, which either means your loan application will be denied, or you'll receive it at a high-interest rate.

Digital lending platforms believe that this kind of information does not paint a complete picture of a loan applicant's credit worthiness. They've taken on to add hundreds and thousands of other data points to their process, not all of which are necessarily related to financial interactions. This can include information such as your educational merits and certifications, employment history, and even trivial information such as when you go to sleep, which websites you browse to, your messaging habits and daily location patterns.

Quick loans are loan products designed to take care of short-term financial difficulties. As the name implies, these loans are disbursed quickly within hours of application. These loans typically have very minimal documentation, and the process is mostly performed online.

Upstart is a California-based peer-to-peer online lending company that is enhancing loans with artificial intelligence. Upstart uses machine learning algorithms, a subset of AI, to make underwriting decisions. Machine learning can analyze and correlate huge amounts of customer data to find patterns that would otherwise require considerable manual effort or go unnoticed to human analysts. For instance, it can determine if applicants are telling the truth about their income by looking through their employment history and comparing their data with that of similar clients. It can also find hidden patterns that might favor an applicant.

Upstart believes this can benefit people with limited credit history, low incomes and young borrowers, who are usually hit with higher interest rates. The company has also managed to automate 25 percent of its less risky loans, a figure it plans to improve over time. This can save a lot of time and energy from lenders, who will welcome a return on investments that requires less intervention on their part. The technology is planned to be available to banks, credit unions and even retailers that are interested in providing low-risk loans to their customers.

Avant, a Chicago-based startup that offers unsecured loans ranging between $1,000 and $35,000, uses analytics and machine learning to streamline borrowing for applicants whose credit score fall below the acceptable threshold of traditional loaning banks. The platform's algorithms analyze 10,000 data points to evaluate the financial situation of consumers. For instance, these algorithms are helping the platform identify applicants who have low FICO scores (below 650) but manifest behavior similar to those with high credit scores.

The company is also using machine learning to detect fraud by comparing customer behavior with the baseline data of normal customers and singling out outliers. The platform analyzes data such as how much time people spend considering application questions, reading contracts or looking at pricing options.Avant is exploring extending its services to brick-and-mortar banks that are interested in starting or expanding their online lending business.

The data can enable companies to create a more complete profile of a loan applicant. This can help make more accurate underwriting decisions, which results in a reduction in defaults for lenders and lower interest rates for borrowers. It can also help automate parts—and maybe all—of the process.

Digital lending reportedly accounts for 10 percent of all loans across US and Europe, a figure that is steadily growing. The benefits of applying machine learning and analytics are evident, and according to CB Insights, there are more than a dozen fintech startups that are using the technology to evaluate loan applications and optimize the process.

However, not everyone agrees that machine learning is the panacea to all the problems of online loans. For instance, many of these applications require to download apps that collect all sorts of personal data. And as the Equifax hack shows, entrusting too much personal information to a single company can have dire security and privacy implications.

There's also the issue of algorithmic bias. Machine learning algorithms too often make decisions that reflect the biases and preferences of the people who provide them with training data. Experts are concerned that this can introduce a whole new set of challenges for loan applicants. And the model has yet to prove its mettle during a downturn or financial crisis.

However, the proponents of machine learning–based loans are confident that AI will eventually become an inherent part of online lending. In an interview with NPR, Dave Girouard, the CEO of Upstart said, "In 10 years, there will hardly be a credit decision made that does not have some flavor of machine learning behind it."

Scope of proposed study

The scope and coverage of this study broadly consists of following aspects,

- Origin and evolution of Artificial intelligence which become an inherent part of online lending
- Detailed understanding of structured loaning formulated by financial regulatory which assist to banks in disbursing loans
- In depth research about the theory, Scientific Steps involved for the disbursement of loan.
- Understanding the profile of individual's day to day activities, structure of organization where they work, obstacles hindering their performance etc.
- Analyzing the impact of Quick/instance loaning on the banks.
- Measuring the revenue growth or cost benefits obtained with the implementation of Artificial Intelligence.

Review of Literature:

- Danaci, E.a, Alkaya, A.F.bGültekin depicted the fact on banking on artificial intelligence, the purpose of this article was to determine the most prominent forms of AI within the banking industry. AI-driven customer service, real-time fraud prevention and risk management-it's the last one that might appeal most to those interested in industry disruption. Deep learning's use of patterns to predict future activity appears to have tremendous potential for stockbrokers, investment bankers, and asset managers to assist them, at least for now.In the study, firstly the aforementioned algorithms are implemented by designing the operators of the algorithms by considering the nature of the problem. Then, parameters of the algorithms are fine-tuned. Predicting the success of ensemble algorithms in the banking sector, the banking sector, like other service sector, improves in accordance with the customer's needs. Therefore, to know the needs of customers and to predict customer behaviors are very important for competition in the banking sector.
- Data obtained via direct marketing campaigns from Portugal Banks was used to classify whether customers have term deposit accounts or not. Through Artificial Neural Networks and Support Vector Machines Fourie, L, Bennett, T.K. has done study on it, Data mining uncovers relationships and hidden patterns in large data sets.
- Dağ, Ö.H.N writes on Super intelligent financial services, this paper provides a contextual overview of the rise of AI and aims to frame AI as not simply a cost-saving auto-motion tool, but as a fundamental shift with many potential considerations, for which the organization must take account. Financial services providers are already utilizing AI to reduce costs, handle compliance pressures, and improve their relationships with customers. Banking and payment services have become fer-tile ground for the implementation of artificial intelligence (AI) solutions to commercial problems.
- Raicu, Irina disclose on Financial Banking Dataset for Supervised Machine Learning Classification, Social media has opened new avenues and opportunities for financial banking institutions to improve the quality of their products and services and to understand and to adapt to their customers' needs. By directly analyzing the feedback of its customers, financial banking institutions can provide personalized products and services tailored to their customer needs. Social Media is used to gather sentiment analysis to tailor banks based off these measures' metrics, As further research, the main objective is to build supervised machine learning classification models for Sentiment Analysis in order to explore opinions insights from financial banking customers. This is particular challenging because the models have to deal with human error.

- Crosman, Penny depicts on the title of the research was "how artificial intelligence is reshaping jobs in banking", jobs that will be lost and gained with the use of AI, the expected front-office jobs that will be dislocated by AI financial managers and compliance officers that will be laid off, and the impact of the introduction by banks of chatbots to do work that might otherwise be done by customer service representatives. 96,000 financial managers and 13,000 compliance officers will laid off as AI-based anti-money-laundering anti- fraud, compliance and monitoring software fills in. Another 250,000 loan officers will lose their jobs. To AI-based credit underwriting and smart banking, 70% of front-office jobs will be dislocated by AI, the researchers say: 485,000 tellers, 219,000 customer, service representatives, and 174,000 loan interviewers and clerks. They will be replaced by chatbots, voice assistants and automated authentication and biometric technology. Contracts technology. Sokolin is less worried about the younger generation than the older generation that might have a harder time shifting to AI-assisted work and who have more at stake with high debt and low savings. 1,300 non executives bank employees, 67% said they believe AI will improve their work-life balance, and 57% expect it will expand their career prospects.
- Mauro Castelli, Luca Manzoni and AlešPopoviI (2016), on the research article, An Artificial Intelligence System to Predict Quality of Service in Banking Organizations. In this paper they propose an artificial intelligence system for predicting the quality of service of a bank. The quality of service has been considered as the waiting time that the user must endure before being served.
- Based on the current level of quality of service, managers can decide to open additional bank counters in order to satisfy customers' request. The application of an artificial intelligence technique tries to overcome the limitations of traditional statistic based linear regression methods. The main problem is that these techniques are unable to adapt to unusual circumstances, which form a highly nonlinear relationship with customers' requests. Hence, their predictions are not as satisfactory as desired.

Al research over the past three decades Credit telephone card providers, companies, mortgage lenders, banks, and the U.S. Government employ AI systems to detect fraud and expedite financial transactions, with daily transaction volumes in the billions. These systems first use learning algorithms to construct profiles of customer usage patterns Work is Developing progressing systems on that converse in natural language, that perceive and respond to their surroundings, and that encode and provide useful access to all of human knowledge and expertise.

The gaps in the research have been identified on the basis of following:

- Meticulous Study of the available research
- Focused discussions with Industry/bank expert consultants who have an elaborate experience in understanding the requirements of the banking industry
- Real time observations and experiences while working as a consultant After an extensive brainstorming, interviews and in depth reading of the literature, the research gaps that have been identified are:
- The banks are focusing towards the loan disbursement on the basis of Artificial Intelligence, which factors are helpful in disbursement
- The biggest pinch that banks face is the crunch of Operational Cash at hand to manage their operational expenses. It is observed that banks follow the traditional and conservative approach for loan disbursement but there is no control on increasing NPA. By investigating through AI, it may reduce the burden of NPA.

The objective of this research is to find out holistic development of the banks and to judge the ability of clients and banks for the utility and disbursement of the quick loan. As it is well known to everyone that banks contribute a large platform of exposure of industrial clients to rural segments. Banks contributes in the economic developments of the nation as well it provides employments and GDP enhancements.

Research identified some objectives of the thesis:

- What is the impact of Quick loan to the banks?
- Understanding the financial contribution of Quick loan to the revenue generation

- Obstacles perceived and current causes that constitutes long process of loan disbursement.
- Does changeover demand a prerequisite AI tool for its effective implementation?
- What is the impact of the Quick loan on the customers and on economy?

Research Methodology:

a. HYPOTHESIS

Following hypothesis have been assumed from this present study:

Research Hypothesis: Effect of Quick and safe loaning (lending of banks) by using Artificial Intelligence on the effectiveness of repayment and collection of loan (reduce in Non-Performing Assets)

H0: There is no significant impact of quick and safe loaning by using AI technique on the effectiveness of banks.

Hypothesis-HA: There is a significant impact of quick and safe loaning by using AI technique on the effectiveness of banks.

The study is divided into further more functionalities for in depth analysis, more subset are formed as:

Hypothesis 1: In the context of Efficiency Improvement

A) H0: There is no significant impact of quick loaning on banks revenue.

H1: There is a significant impact of quick loaning on banks revenue

B) H0: There is no significant impact of quick loaning after analyzing through AI tool on the NPA of the banks

H1: There is no significant impact of quick loaning after analyzing through AI tool on the NPA of the banks

Hypothesis 2: In the context of utility:

A) H0: There is no significant impact of quick loaning on the demand and supply function.

H1: There is no significant impact of quick loaning on the demand and supply function.

Hypothesis 3: In the context to dependence on other disbursement Tools of loaning:

A) H0: Quick loaning is based on AI analysis is totally independent from other tools of disbursement of loaning to deliver effective results

H1: Quick loaning is based on AI analysis is totally independent from other tools of disbursement of loaning to deliver effective results

B. SOURCES OF INFORMATION:

Information gathering is done by collecting data and then processing it into information. The data will be gathered from two sources:

- Primary Sources
- Secondary Sources

The Primary sources of information include:

- Questionnaire's, that would collect data from a strategically identified group that includes Organizations, Entrepreneurs ,Industry experts ,Consultants that have been actively involved in the implementation of Quick Changeover as a Lean tool.
- In –Depth interviews with bankers, Industry Experts and Consultants, Educationist.
- Focus Group that will include a cross functional group of Subject Matter
- Experts, Educationists, Entrepreneurs, Managers.

A few of the Secondary sources of information include:

- EBSCO host for International Journals, articles, research papers.
- Core is a multidisciplinary aggregator of open access research. It allows users to have open access articles
- Directory of Open Access Journals for international Journals
- India Stat.com to substantiate the stats used in the research
- CMIE Industry Outlook for the forecast
- Gartner industry reports

Hypothesis Testing

Hypothesis 1: In the context of Efficiency Improvement

A) H0: There is no significant impact of quick loaning on banks revenue.

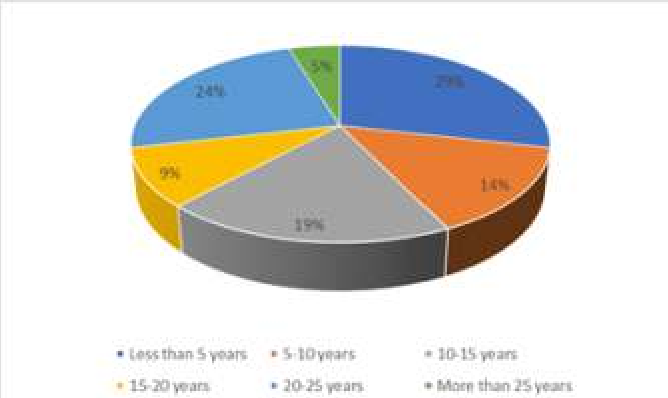
H1: There is a significant impact of quick loaning on banks revenue

Experience

Descriptive
Revenue

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Minimum	Maximum	Between-Component Variance
Less than 5 years		78	5.00	0.000	0.000	5.00	5.00	5	5	
5-10 years		39	4.67	.478	.076	4.51	4.82	4	5	
10-15 years		52	5.00	0.000	0.000	5.00	5.00	5	5	
15-20 years		26	3.50	.510	.100	3.29	3.71	3	4	
20-25 years		65	3.40	1.209	.150	3.10	3.70	2	5	
More than 25 years		13	5.00	0.000	0.000	5.00	5.00	5	5	
Total		273	4.43	.957	.058	4.31	4.54	2	5	
Model	Fixed Effects			.638	.039	4.35	4.50			
	Random Effects				.365	3.49	5.37			.637

The respondents of various groups (experience in banking services) were asked that revenue of the bank will increase after implementation of quick loan to customers through bank branches. Descriptive analysis shows that 29% respondents having less than 5 years of experience strongly agreed that there is a significant impact of quick loaning on banks revenue, same opinion was among 10-15 years and more than 25 years of experience in banking sectors as an employee.



ANOVA

Revenue

			Sum of Squares	df	Mean Square	F	Sig.
Between Groups	(Combined)		140.090	5	28.018	68.779	.000
	Linear Term	Unweighted	10.519	1	10.519	25.821	.000
		Weighted	72.621	1	72.621	178.269	.000
		Deviation	67.470	4	16.867	41.406	.000
Within Groups			108.767	267	.407		
Total			248.857	272			

F value is 68.779 and significant P value is less than .05 indicates that Null hypothesis that there is no significant impact of quick loaning on banks revenue cannot be accepted. This conclude the alternate hypothesis, there is significant impact of quick loaning on banks revenue as per experience group of bank employees hereby. Young employees those who have less than 5 years of experience as well 10-15 years and 25 years of experience realize that there is significant impact of quick loaning on bank revenue

Multiple Comparisons							
Dependent Variable: revenue							
(I) experience			Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
LSD	1	2	.333*	.125	.008	.09	.58
		3	0.000	.114	1.000	-.22	.22
		4	1.500*	.145	.000	1.22	1.78
		5	1.600*	.107	.000	1.39	1.81
		6	0.000	.191	1.000	-.38	.38
	2	1	-.333*	.125	.008	-.58	-.09
		3	-.333*	.135	.014	-.60	-.07
		4	1.167*	.162	.000	.85	1.48
		5	1.267*	.129	.000	1.01	1.52
		6	-.333	.204	.104	-.74	.07
	3	1	0.000	.114	1.000	-.22	.22
		2	.333*	.135	.014	.07	.60
		4	1.500*	.153	.000	1.20	1.80
		5	1.600*	.119	.000	1.37	1.83
		6	0.000	.198	1.000	-.39	.39
	4	1	-1.500*	.145	.000	-1.78	-1.22
		2	-1.167*	.162	.000	-1.48	-.85
		3	-1.500*	.153	.000	-1.80	-1.20
		5	.100	.148	.500	-.19	.39
		6	-1.500*	.217	.000	-1.93	-1.07
	5	1	-1.600*	.107	.000	-1.81	-1.39
		2	-1.267*	.129	.000	-1.52	-1.01
		3	-1.600*	.119	.000	-1.83	-1.37
		4	-.100	.148	.500	-.39	.19
		6	-1.600*	.194	.000	-1.98	-1.22
	6	1	0.000	.191	1.000	-.38	.38
		2	.333	.204	.104	-.07	.74
		3	0.000	.198	1.000	-.39	.39
		4	1.500*	.217	.000	1.07	1.93
		5	1.600*	.194	.000	1.22	1.98

Multiple Comparisons							
Dependent Variable: revenue							
Tamhane	1	2	.333*	.076	.001	.09	.57
		3	0.000	0.000		0.00	0.00
		40	1.500*	.100	.000	1.18	1.82
		5	1.600*	.150	.000	1.14	2.06
		6	0.000	0.000		0.00	0.00
	2	1	-.333*	.076	.001	-.57	-.09
		3	-.333*	.076	.001	-.57	-.09
		4	1.167*	.126	.000	.78	1.55
		5	1.267*	.168	.000	.76	1.77
		6	-.333*	.076	.001	-.57	-.09
	3	1	0.000	0.000		0.00	0.00
		2	.333*	.076	.001	.09	.57
		4	1.500*	.100	.000	1.18	1.82
		5	1.600*	.150	.000	1.14	2.06
		6	0.000	0.000		0.00	0.00
	4	1	-1.500*	.100	.000	-1.82	-1.18
		2	-1.167*	.126	.000	-1.55	-.78
		3	-1.500*	.100	.000	-1.82	-1.18
		5	.100	.180	1.000	-.44	.64
		6	-1.500*	.100	.000	-1.82	-1.18
	5	1	-1.600*	.150	.000	-2.06	-1.14
		2	-1.267*	.168	.000	-1.77	-.76
		3	-1.600*	.150	.000	-2.06	-1.14
		4	-.100	.180	1.000	-.64	.44
		6	-1.600*	.150	.000	-2.06	-1.14
	6	1	0.000	0.000		0.00	0.00
		2	.333*	.076	.001	.09	.57
		3	0.000	0.000		0.00	0.00
		4	1.500*	.100	.000	1.18	1.82
		5	1.600*	.150	.000	1.14	2.06

*. The mean difference is significant at the 0.05 level.

At the 0.05 significant level, the mean difference between group 1, group 2, group 4 and group 5, and this interval does not contain 0, that the difference between these fourgroups mean is statistically significant. The lower bound at the 95% confidence level is greater than zero and positive.

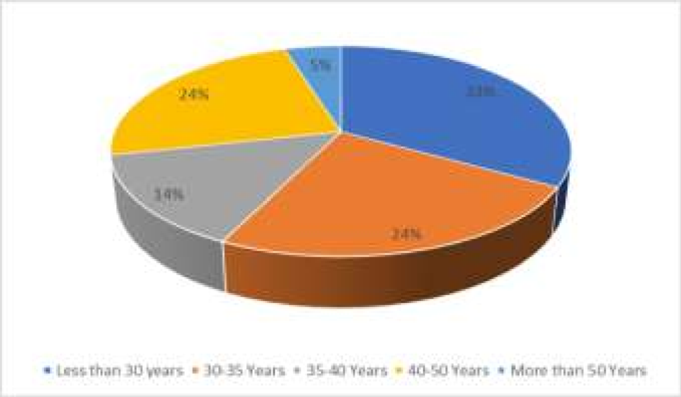
The p-value for the mean difference between group 1, group 2, group 4 and group 5 is less than 0.05, this also indicates that the difference between these four groups means is statistically significant.

Similarly, group 2 and rest of all group means are highly statistically significant.

Age

Descriptive
Revenue

						95% Confidence Interval for Mean				
		N	Mean	Std. Deviation	Std. Error	Lower Bound	Upper Bound	Minimum	Maximum	Between-Component Variance
1		91	5.00	0.000	0.000	5.00	5.00	5	5	
2		65	5.00	0.000	0.000	5.00	5.00	5	5	
3		39	3.67	.478	.076	3.51	3.82	3	4	
4		65	3.40	1.209	.150	3.10	3.70	2	5	
5		13	5.00	0.000	0.000	5.00	5.00	5	5	
Total		273	4.43	.957	.058	4.31	4.54	2	5	
Model	Fixed Effects			.618	.037	4.35	4.50			
	Random Effects				.419	3.26	5.59			.706



The respondents of various groups (age of the respondents in banking services) were asked that revenue of the bank will increase after implementation of quick loan to customers through bank branches. Descriptive analysis shows that 33% respondents having less than 30 years of age strongly agreed that there is a significant impact of quick loaning on banks revenue, same opinion was among 30-35 years and 40 to 50 years of age in banking sectors as an employee.

Anova
Revenue

			Sum of Squares	Df	Mean Square	F	Sig.
Between Groups	(Combined)		146.590	4	36.648	96.039	.000
	Linear Term	Unweighted	6.694	1	6.694	17.543	.000
		Weighted	81.654	1	81.654	213.982	.000
		Deviation	64.937	3	21.646	56.724	.000
Within Groups			102.267	268	.382		
Total			248.857	272			

F value is 96.039 and significant P value is less than .05 indicates that Null hypothesis that there is no significant impact of quick loaning on banks revenue cannot be accepted as per the age of the employees. This conclude the alternate hypothesis, there is significant impact of quick loaning on banks revenue as per different age groups of bank employees hereby. Young employees those who have less than 30 years of experience as well 30-35 years of age and 40-50 years of age realize that there is significant impact of quick loaning on bank revenue.

Post Hoc Tests
Multiple Comparisons

Dependent Variable: revenue							
						95% Confidence Interval	
(I) age			Mean Difference (I-J)	Std. Error	Sig.	Lower Bound	Upper Bound
LSD	1	2	0.000	.100	1.000	-.20	.20
		3	1.333*	.118	.000	1.10	1.57
		4	1.600*	.100	.000	1.40	1.80
		5	0.000	.183	1.000	-.36	.36
	2	1	0.000	.100	1.000	-.20	.20
		3	1.333*	.125	.000	1.09	1.58
		4	1.600*	.108	.000	1.39	1.81
		5	0.000	.188	1.000	-.37	.37
	3	1	-1.333*	.118	.000	-1.57	-1.10
		2	-1.333*	.125	.000	-1.58	-1.09
		4	.267*	.125	.034	.02	.51
		5	-1.333*	.198	.000	-1.72	-.94
	4	1	-1.600*	.100	.000	-1.80	-1.40
		2	-1.600*	.108	.000	-1.81	-1.39
		3	-.267*	.125	.034	-.51	-.02
		5	-1.600*	.188	.000	-1.97	-1.23
	5	1	0.000	.183	1.000	-.36	.36
		2	0.000	.188	1.000	-.37	.37
		3	1.333*	.198	.000	.94	1.72
		4	1.600*	.188	.000	1.23	1.97
Tamhane	1	2	0.000	0.000		0.00	0.00
		3	1.333*	.076	0.000	1.11	1.56
		4	1.600*	.150	.000	1.17	2.03
		5	0.000	0.000		0.00	0.00
	2	1	0.000	0.000		0.00	0.00
		3	1.333*	.076	0.000	1.11	1.56
		4	1.600*	.150	.000	1.17	2.03
		5	0.000	0.000		0.00	0.00
	3	1	-1.333*	.076	0.000	-1.56	-1.11
		2	-1.333*	.076	0.000	-1.56	-1.11
		4	.267	.168	.711	-.22	.75
		5	-1.333*	.076	0.000	-1.56	-1.11

Dependent Variable: revenue								
(I) age			Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
	4	1	-1.600*	.150	.000	-2.03	-1.17
		2	-1.600*	.150	.000	-2.03	-1.17
		3	-.267	.168	.711	-.75	.22
		5	-1.600*	.150	.000	-2.03	-1.17
	5	1	0.000	0.000		0.00	0.00
		2	0.000	0.000		0.00	0.00
		3	1.333*	.076	0.000	1.11	1.56
		4	1.600*	.150	.000	1.17	2.03

*. The mean difference is significant at the 0.05 level.

At the 0.05 significant level, the mean difference between group 1, group 3 and group 4, and this interval does not contain 0, that the difference between these three groups mean is statistically significant. The lower bound at the 95% confidence level is greater than zero and positive.

The p-value for the mean difference between group 1, group 3 and group 4 is less than 0.05, this also indicates that the difference between these three groups means is statistically significant.

Similarly, group 2 paired with group 3 and 4 means are highly statistically significant.

B) H0: There is no significant impact of quick loaning after analyzing through AI tool on the NPA of the banks

H1: There is no significant impact of quick loaning after analyzing through AI tool on the NPA of the banks

Kruskal-Wallis Test

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
Reduce NPA	273	3.9048	.86925	2.00	5.00
Age	273	2.43	1.296	1	5

Ranks

Age		N	Mean Rank
Reduce NPA	1	91	181.57
	2	65	133.10
	3	39	35.17
	4	65	118.80
	5	13	241.00
	Total	273	

There is a mean difference between all the age group of the employees, age group having less than 30 years have mean rank of 181.57, 30-35 years of age have 133.10, 35-40 years of age having mean rank 35.17, 40-50 years of age having mean rank 118.80 and above 50 years age having the mean rank of 241.00.

Test Statisticsa,b

	Reduce NPA
Chi-Square	143.086
Df	4
Asymp. Sig.	.000

a. Kruskal Wallis Test
b. Grouping Variable:age

Chi-square value 143.086 indicate that null hypothesis is rejected that there is no significant impact of quick loaning after analyzing through AI tool on the NPA of the banks can not be accepted. This conclude the alternate hypotheses, there is a significant impact of quick loaning after analyzing through AI tool on the NPA of the banks

Hypothesis 2: In the context of utility:

A) H0: There is no significant impact of quick loaning on the demand and supply function.

H1: There is a significant impact of quick loaning on the demand and supply function.

Descriptives Demand supply

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum	Between-Component Variance
						Lower Bound	Upper Bound			
Less than 30 years		91	4.71	.454	.048	4.62	4.81	4	5	
30-35 Years		65	3.60	1.367	.170	3.26	3.94	2	5	
35-40 Years		39	3.33	.955	.153	3.02	3.64	2	4	
40-50 Years		65	3.60	.494	.061	3.48	3.72	3	4	
More than 50 Years		13	5.00	0.000	0.000	5.00	5.00	5	5	
Total		273	4.00	1.025	.062	3.88	4.12	2	5	
Model	Fixed Effects			.839	.051	3.90	4.10			
	Random Effects				.341	3.05	4.95			.461

The respondents of various groups (age of the respondents in banking services) were asked, Is there any impact of quick loaning on the demand and supply function? Descriptive analysis shows that 33% respondents having less than 50 years of age strongly agreed that there is a significant impact of quick loaning on demand and supply function, same opinion was among the age group of less than 30 years.

ANOVA
Demand supply

			Sum of Squares	Df	Mean Square	F	Sig.
Between Groups	(Combined)		97.562	4	24.390	34.689	.000
	Linear Term	Unweighted	.854	1	.854	1.214	.271
		Weighted	23.675	1	23.675	33.671	.000
		Deviation	73.887	3	24.629	35.028	.000
Within Groups			188.438	268	.703		
Total			286.000	272			

F value is 34.689 and significant P value 0.000 is less than .05 indicates that Null hypothesis, there is no significant impact of quick loaning on demand and supply function cannot be accepted as per the age of the employees. This conclude the alternate hypothesis, there is a significant impact of quick loaning on demand and supply function as per opinion of different age groups of bank employees hereby. Young employees those who have more than 50 years of experience as well less than 30 years of age think that there is significant impact of quick loaning on demand and supply function.

Multiple Comparisons

Dependent Variable: revenue							
(I) age			Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
LSD	1	2	0.000	.100	1.000	-.20	.20
		3	1.333*	.118	.000	1.10	1.57
		4	1.600*	.100	.000	1.40	1.80
		5	0.000	.183	1.000	-.36	.36
	2	1	0.000	.100	1.000	-.20	.20
		3	1.333*	.125	.000	1.09	1.58
		4	1.600*	.108	.000	1.39	1.81
		5	0.000	.188	1.000	-.37	.37
	3	1	-1.333*	.118	.000	-1.57	-1.10
		2	-1.333*	.125	.000	-1.58	-1.09
		4	.267*	.125	.034	.02	.51
		5	-1.333*	.198	.000	-1.72	-.94
	4	1	-1.600*	.100	.000	-1.80	-1.40
		2	-1.600*	.108	.000	-1.81	-1.39
		3	-.267*	.125	.034	-.51	-.02
		5	-1.600*	.188	.000	-1.97	-1.23
	5	1	0.000	.183	1.000	-.36	.36
		2	0.000	.188	1.000	-.37	.37
		3	1.333*	.198	.000	.94	1.72
		4	1.600*	.188	.000	1.23	1.97
Tamhane	1	2	0.000	0.000		0.00	0.00
		3	1.333*	.076	0.000	1.11	1.56
		4	1.600*	.150	.000	1.17	2.03
		5	0.000	0.000		0.00	550.00
	2	1	0.000	0.000		0.00	0.00
		3	1.333*	.076	0.000	1.11	1.56
		4	1.600*	.150	.000	1.17	2.03
		5	0.000	0.000		0.00	0.00
	3	1	-1.333*	.076	0.000	-1.56	-1.11
		2	-1.333*	.076	0.000	-1.56	-1.11
		4	.267	.168	.711	-.22	.75
		5	-1.333*	.076	0.000	-1.56	-1.11
	4	1	-1.600*	.150	.000	-2.03	-1.17
		2	-1.600*	.150	.000	-2.03	-1.17
		3	-.267	.168	.711	-.75	.22
		5	-1.600*	.150	.000	-2.03	-1.17
	5	1	0.000	0.000		0.00	0.00
		2	0.000	0.000		0.00	0.00
		3	1.333*	.076	0.000	1.11	1.56
		4	1.600*	.150	.000	1.17	2.03
*. The mean difference is significant at the 0.05 level.							

At the 0.05 significant level, the mean difference between group 1and group 5, and this interval does not contain 0, that the difference between these two groups mean is statistically significant. The lower bound at the 95% confidence level is greater than zero and positive.

The p-value for the mean difference between group 1and group 2 is less than 0.05, this also indicates that the difference between these two groups means is statistically significant.

Similarly, group 2 paired with group 3 and 4 means are highly statistically significant. The p-value for the mean difference between group 2, group 3 and group 4 is less than 0.05, this also indicates that the difference between these two groups means is statistically significant.

Descriptive

Demand supply										
		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum	Between-Component Variance
						Lower Bound	Upper Bound			
Less than 5 years		78	4.83	.375	.042	4.75	4.92	4	5	
5-10 years		39	4.00	0.000	0.000	4.00	4.00	4	4	
10-15 years		52	3.50	1.515	.210	3.08	3.92	2	5	
15-20 years		26	3.00	1.020	.200	2.59	3.41	2	4	
20-25 years		65	3.60	.494	.061	3.48	3.72	3	4	
More than 25 years		13	5.00	0.000	0.000	5.00	5.00	5	5	
Total		273	4.00	1.025	.062	3.88	4.12	2	5	
Model	Fixed Effects			.797	.048	3.91	4.09			
	Random Effects				.332	3.15	4.85			.523

The respondents of various groups (experience in banking services) were asked that Is there any impact of quick loaning on the demand and supply function? Descriptive analysis shows that respondents having more than 25 years of experience strongly agreed that there is a significant impact of quick loaning on demand and supply function, same opinion was among less than years of experience in banking sectors as an employee.

ANOVA

Demand supply							
			Sum of Squares	Df	Mean Square	F	Sig.
Between Groups	(Combined)		116.567	5	23.313	36.738	.000
	Linear Term	Unweighted	.281	1	.281	.443	.506
		Weighted	37.879	1	37.879	59.692	.000
		Deviation	78.687	4	19.672	31.000	.000
Within Groups			169.433	267	.635		
Total			286.000	272			

F value is 36.738 and significant P value 0.000 is less than .05 indicates that Null hypothesis, there is no significant impact of quick loaning on demand and supply function cannot be accepted as per the experience of the employees. This conclude the alternate hypothesis, there is a significant impact of quick loaning on demand and supply function as per opinion of different various experience groups of bank employees hereby. Employees those who have more than 25 years of experience as well less than 5 years of experience, they think that there is significant impact of quick loaning on demand and supply function.

Post Hoc Tests

Multiple Comparisons

Dependent Variable: demandsupply							
(I) experience			Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
LSD	1	2	.833*	.156	.000	.53	1.14
		3	1.333*	.143	.000	1.05	1.61
		4	1.833*	.180	.000	1.48	2.19
		5	1.233*	.134	.000	.97	1.50
		6	-.167	.239	.486	-.64	.30
	2	1	-.833*	.156	.000	-1.14	-.53
		3	.500*	.169	.003	.17	.83
		4	1.000*	.202	.000	.60	1.40
		5	.400*	.161	.014	.08	.72
		6	-1.000*	.255	.000	-1.50	-.50
	3	1	-1.333*	.143	.000	-1.61	-1.05
		2	-.500*	.169	.003	-.83	-.17
		4	.500*	.191	.009	.12	.88
		5	-.100	.148	.500	-.39	.19
		6	-1.500*	.247	.000	-1.99	-1.01
	4	1	-1.833*	.180	.000	-2.19	-1.48
		2	-1.000*	.202	.000	-1.40	-.60
		3	-.500*	.191	.009	-.88	-.12
		5	-.600*	.185	.001	-.96	-.24
		6	-2.000*	.271	.000	-2.53	-1.47
	5	1	-1.233*	.134	.000	-1.50	-.97
		2	-.400*	.161	.014	-.72	-.08
		3	.100	.148	.500	-.19	.39
		4	.600*	.185	.001	.24	.96
		6	-1.400*	.242	.000	-1.88	-.92
	6	1	.167	.239	.486	-.30	.64
		2	1.000*	.255	.000	.50	1.50
		3	1.500*	.247	.000	1.01	1.99
		4	2.000*	.271	.000	1.47	2.53
		5	1.400*	.242	.000	.92	1.88
Tamhane	1	2	.833*	.042	0.000	.71	.96
		3	1.333*	.214	.000	.68	1.99
		4	1.833*	.204	.000	1.18	2.49
		5	1.233*	.075	0.000	1.01	1.46
		6	-.167*	.042	.003	-.29	-.04

Dependent Variable: demandsupply							
(I) experience			Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
	2	1	-.833*	.042	0.000	-.96	-.71
		3	.500	.210	.273	-.15	1.15
		4	1.000*	.200	.001	.35	1.65
		5	.400*	.061	.000	.21	.59
		6	-1.000	0.000		-1.00	-1.00
	3	1	-1.333*	.214	.000	-1.99	-.68
		2	-.500	.210	.273	-1.15	.15
		4	.500	.290	.754	-.38	1.38
		5	-.100	.219	1.000	-.77	.57
		6	-1.500*	.210	.000	-2.15	-.85
	4	1	-1.833*	.204	.000	-2.49	-1.18
		2	-1.000*	.200	.001	-1.65	-.35
		3	-.500	.290	.754	-1.38	.38
		5	-.600	.209	.107	-1.27	.07
		6	-2.000*	.200	.000	-2.65	-1.35
	5	1	-1.233*	.075	0.000	-1.46	-1.01
		2	-.400*	.061	.000	-.59	-.21
		3	.100	.219	1.000	-.57	.77
		4	.600	.209	.107	-.07	1.27
		6	-1.400*	.061	0.000	-1.59	-1.21
	6	1	.167*	.042	.003	.04	.29
		2	1.000	0.000		1.00	1.00
		3	1.500*	.210	.000	.85	2.15
		4	2.000*	.200	.000	1.35	2.65
		5	1.400*	.061	0.000	1.21	1.59
*. The mean difference is significant at the 0.05 level.							

At the 0.05 significant level, the mean difference between group 1 to group 5, and this mean interval does not contain 0, that the difference between these 1 to 5 groups mean is statistically significant. The lower bound at the 95% confidence level is greater than zero and positive.

The p-value for the mean difference between group 1 to group 5 is less than 0.05, this also indicates that the difference between these five groups means is statistically significant.

Similarly, group 2 paired with group 1 and 5 means are highly statistically significant. The p-value for the mean difference between group 2, group 1 and group 5 is less than 0.05, this also indicates that the difference between these three groups means is statistically significant.

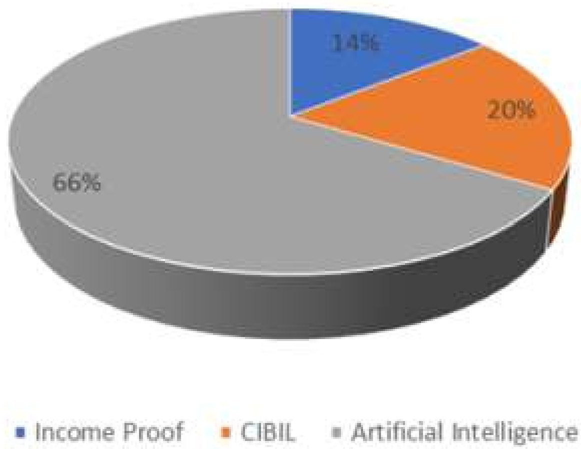
Hypothesis 3: In the context to dependence on other disbursement Tools of loaning:

A) H0: Quick loaning is based on AI analysis is totally independent from other tools of disbursement of loaning to deliver effective results

H1: Quick loaning is based on AI analysis is totally independent from other tools of disbursement of loaning to deliver effective results

AI analysis

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Income Proof	39	14.3	14.3	14.3
	CIBIL	53	19.4	19.4	33.7
	Artificial Intelligence	181	66.3	66.3	100.0
	Total	273	100.0	100.0	



Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
experience * AI analysis	273	100.0%	0	0.0%	273	100.0%

experience * AI analysis Cross tabulation

Count					
		AI analysis			Total
		Income Proof	CIBIL	Artificial Intelligence	
Experience	1	25_a	14_b	39_b	78
	2	0_a	10_b	29_b	39
	3	7_a	15_a	30_a	52
	4	1_a	8_b	$17_{a, b}$	26
	5	2_a	5_a	58_b	65
	6	4_a	1_a	8_a	13
Total		39	53	181	273

Each subscript letter denotes a subset of AI analysis categories whose column proportions do not differ significantly from each other at the .05 level.

Above cross table indicates that there is opinion difference among all experienced group of bank employee of all the thirteen banks. Majority of bankers employee 181 out of 273 employees think that AI analysis is totally independent from other tools of disbursement of loaning to deliver effective results in comparison with income proof and CIBIL information.

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	52.788[a]	10	.000
Likelihood Ratio	57.539	10	.000
Linear-by-Linear Association	17.005	1	.000
N of Valid Cases	273		
a. 3 cells (16.7%) have expected count less than 5. The minimum expected count is 1.86.			

Pearson Chi-square value 52.788 at 10 degree of freedom and P value is 0.000 which is less than .05 indicates that value are significant and the experience group of employee have different opinion related to AI analysis is totally independent from other tools of disbursement of loaning to deliver effective results. The null hypothesis, AI analysis is totally independent from other tools of disbursement of loaning to deliver effective results can not be accepted and alternate hypothesis concludes that AI analysis is totally dependent from other tools of disbursement of loaning to deliver effective results.

Directional Measures

			Value
Nominal by Interval	Eta	experience Dependent	.250
		AI analysis Dependent	.367

Symmetric Measures

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Nominal by Nominal	Contingency Coefficient	.403			.000
Interval by Interval	Pearson's R	.250	.062	4.251	.000[c]
Ordinal by Ordinal	Spearman Correlation	.254	.060	4.320	.000[c]
N of Valid Cases		273			
a. Not assuming the null hypothesis.					
b. Using the asymptotic standard error assuming the null hypothesis.					
c. Based on normal approximation.					

The above nominal by nominal and contingency coefficient indicates the value 0.403 is higher and significant which authenticate the result of chi-square test. Results shows that artificial intelligence will play important role in disbursement of quick loan.

age * AI analysis Crosstabulation					
Count					
		AI analysis			Total
		Income Proof	CIBIL	Artificial Intelligence	
Age	1	25_a	16_b	50_b	91
	2	7_a	22_b	36_a	65
	3	1_a	9_b	29_b	39
	4	2_a	5_a	58_b	65
	5	4_a	1_a	8_a	13
Total		39	53	181	273

Each subscript letter denotes a subset of AI analysis categories whose column proportions do not differ significantly from each other at the .05 level.

Above cross table indicates that there is opinion difference among all age group of bank employee of all the thirteen banks. Majority of bankers employee 181 out of 273 employees think that AI analysis is totally independent from other tools of disbursement of loaning to deliver effective results in comparison with income proof and CIBIL information. The majority is among age between 40-50 age group and less than 30 years of age think and strongly believe in it.

Chi-Square Tests			
	Value	Df	Asymp. Sig. (2-sided)
Pearson Chi-Square	45.020[a]	8	.000
Likelihood Ratio	46.767	8	.000
Linear-by-Linear Association	17.823	1	.000
N of Valid Cases	273		

a. 2 cells (13.3%) have expected count less than 5. The minimum expected count is 1.86.

Pearson Chi-square value 45.020 at 8 degrees of freedom and P value is 0.000 which is less than .05 indicates that values are significant and the various age groups of employee have different opinion related to AI analysis is totally independent from other tools of disbursement of loaning to deliver effective results. The null hypothesis, AI analysis is totally independent from other tools of disbursement of loaning to deliver effective results can not be accepted and alternate hypothesis concludes that AI analysis is totally dependent from other tools of disbursement of loaning to deliver effective results.

Directional Measures			
			Value
Nominal by Interval	Eta	age Dependent	.258
		AIanalysis Dependent	.326

Symmetric Measures					
		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Nominal by Nominal	Contingency Coefficient	.376			.000
Interval by Interval	Pearson's R	.256	.061	4.359	.000[c]
Ordinal by Ordinal	Spearman Correlation	.262	.059	4.477	.000[c]
N of Valid Cases		273			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

c. Based on normal approximation.

The above nominal by nominal and contingency coefficient indicates the value 0.403 is higher and significant which authenticate the result of chi-square test. Results shows that artificial intelligence will play important role in disbursement of quick loan.

Conclusions:

Through the respondents, it is observed that utility of AI will have greater impact on banking services and banks need to improve their IT sector immediately to offer best services to the customers.

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