An Empirical Analysis on Facilitators and Inhibitors of Bankers' Intention to Use Artificial Intelligence Applications in Delhi/NCR

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[Abstract] The twenty-first century has witnessed drastic transformation in the financial sector as financial disruption has caused adjustments in the ever-changing banking industry. Banks are looking for innovative ways to handle massive numbers of transactions per day.
The main objective of the study is to determine the impact of the facilitators and inhibitors on bankers' behaviors and perceptions of using AI applications by considering an extension in the UTAUT model to include risk, perceived complexity, and technological anxiety.

The extended UTAUT model was assessed using a final sample of 108 bankers. The study is based on primary data through a structured questionnaire circulated in bank branches of Delhi / NCR. A questionnaire using seven factors (performance expectancy, effort expectancy, social influence, risk, technological anxiety, perceived complexity and behavioral intention) was used. The data is investigated to test the hypothesis using statistical tools such as reliability, KMO, and Bartlett's test of sphericity, exploratory factor analysis, regression, and analysis of variance (ANOVA) of the instrument items. The results estimated using a multiple regression analysis showed that social influence and risk play a significant role in understanding bankers' intention to use AI applications. The results further showed characteristics, such as age, education, gender, and the type of banks, through pie diagrams and descriptive frequency charts.

[Keywords] artificial intelligence applications, behavioral intention to use, UTAUT, perceived complexity, technological anxiety, risk, social influence, Delhi/NCR

Introduction

The exponential rise in digital technologies and internet use has significantly contributed to the growth of the global AI market in past few years. Huge investments are made by technology moguls in research who are continuously leading advancements in various sectors. The escalating demand for artificial intelligence technology among the various end users, such as automotive, healthcare, finance and banking, manufacturing, food and beverages, logistics, and retailers, is expected to significantly grow. The rising adoption of AI applications in the banking industry is expected to further fuel the growth of Indian economy. As per the famous saying, necessity is the mother of all inventions. Bank customers are becoming more and more demanding regarding the products and services they require. Technology disruption and changes in customer preferences are laying the basis for the modern banking era.

With the use of super powered AI technologies, banks have the potential to increase revenue at lower costs by providing seamless operations and predictive analytics. To leverage the increased technological advancement and demand for personal insights from customers, the banking industry should adopt artificial intelligence and powered technologies and unite them into their business strategies and objectives. Traditional banks are facing multiple challenges, such as unsatisfied customers, huge bad debt, increased costs, and others. Further, they are also facing stiff competition from Fintech companies. Leading private banks in India are already taking advantage of cutting-edge technology offered by AI, such as predictive analytics, virtual assistants, trading with AI-based algorithms, and many more. With the growth in technology, customers are showing an exponential increase in digital channels, and they are becoming accustomed to speed, ease, and personalized services offered by banks. The banking industry is presently undergoing a massive transformation due to the onset of artificial intelligence banking applications. Banks have started using AI applications in theory work processes, such as AI software robots processing loan applications in less a second. Robo advisors analyze the real time data available in social media, e-mail and news regarding diverse sectors and provide valuable suggestions on investment in various sectors. The immense power has been utilized by banks to offer personalized business solutions in front-window and back-end operational processes to create higher levels of efficiency and improve customers' overall experience (Donepudi, 2017).

Literature Review

Now, with the banking industry's priority shifting from comfort and growth to stability and survival, creating a holistic customer experience and understanding of the financial needs of consumers is even more critical. The business model of the banks has been challenged by three developments: low interest rates affecting the profitability of banks, increased regulatory requirements and compliance costs, and massive application of the latest technologies (Elena Carletti, 2020). Since banks play a very important role in the economic development of the entire country, the use of the latest technology to successfully implement and implement strategies will not only create added value for one's own business, but also contribute to the economy and growth of the country. Banks must keep pace with the ever-increasing expectations of today's rapidly changing environment. Banking products have far surpassed traditional banking in India (Kurode, 2018). Traditional banking continues to evolve, and banks have gradually introduced innovative technologies, such as AI, block chain, and cloud computing.

The Indian banking industry is looking for ways to integrate artificial intelligence that can improve customer service and banking in the near future (Jewandah, 2018). Currently, artificial Intelligence technology has had a huge impact in many industries, such as healthcare, oil and gas construction, retail, and manufacturing. The latest technologies have been used to improve efficiency, reduce costs, and offer a wide range of commercial benefits (Dubey, 2019). The bank uses AI-based anti-money laundering, anti-fraud, compliant credit underwriting, and smart contract technologies in its operations. In order to improve profitability and improve the quality of the decisions made at different management levels (Vedapradha, 2018), employees are reserved for innovation and implementation of the expected strategies that are in line with the original vision and the macroeconomic situation. Currently, the bank's employees perform many repetitive, unproductive tasks, and skilled human resources are limited due to their creative and high-level decision-making role (Kurode, 2018).

Artificial intelligence has become mainstream in large numbers these days. Companies and start-ups are looking for different opportunities. Artificial intelligence adoption is still in its infancy and more needs to be done to achieve its full potential. (N. & B.R., 2019). Not only does artificial Intelligence (AI) play an important role in customer satisfaction, but fraud detection also plays an important role in finance and banking, especially due to the Covid-19 pandemic. India's digital banking is largely being adopted (RBI Report, 2020). An article discussed the practical uses of artificial intelligence in various aspects of banking, e.g. monitoring, fraud detection, ensuring compliance with regulations, credit checks, customer service, coping with monotonous and difficult tasks, etc. (Aggarwal et al, 2019). However, it is much easier to formulate a strategy than to execute it successfully in India. Artificial intelligence (AI) can play a critical role in customer satisfaction and fraud detection in the finance and banking industry, especially as digital banking is seeing major adoption in India due to the covid-19 pandemic (RBI Report, 2020). One of the articles talks about practical application of artificial Intelligence in various aspects of banking operations such as surveillance, fraud detection, ensuring compliances, credit assessment, customer service, handling monotonous voluminous tasks, etc. (Aggarwal et al, 2019). According to the latest statistics, US $ 1.3 billion has been invested in financial technology projects worldwide (Dubey, 2019).

Gap Analysis

On the basis of existing literature, certain gaps have been identified. Artificial intelligence technology in Indian banking is an underexplored area. There is lot of literature available on the use and adoption of AI technology with respect to developed nations. The previous research talks about AI in banking in other nations, such as AI improving banking performance in middle east countries (Alzaidi, Oct 2018), and RPA in banking with respect to foreign banks (Villar & Khan, 2021). The purpose of this study is to determine the factors that affect the bankers' behavior and intentions in banking in India. There are few studies which talk about bankers' intention to use latest technologies, but this research is the first of its kind in which bankers' perceptions have been studied from the point of two different drivers, that is facilitators and inhibitors, which are impacting bankers' perceptions to use AI. The research in this area is inadequate and scarce.

Research Questions

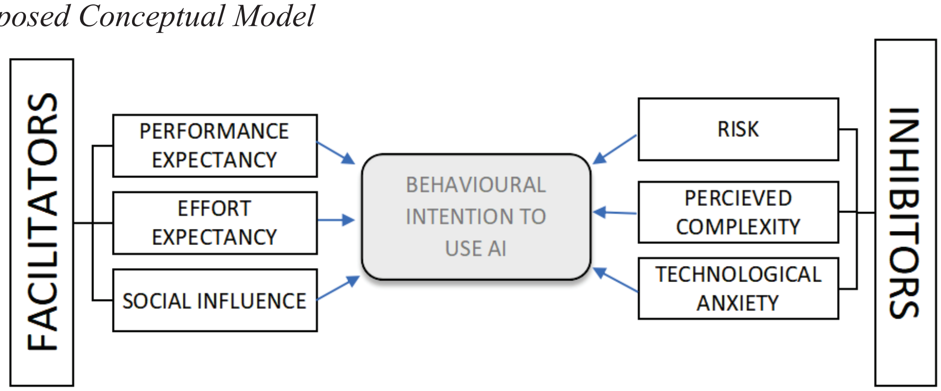
Question1: Do facilitators, such as performance expectancy, effort expectancy, and social influence behavior affect the intention of bankers to use AI in banking?
Question2: Do inhibitors, namely risk, perceived complexity, and technological anxiety, influence the behavior and intention of bankers to use AI in banking?
On the basis of analysis of research questions, the authors formulate the following objectives for the research paper:

Objectives Of The Study

1. To determine whether the potential factors that facilitate and inhibit influence the behavior and intention of bankers to use AI in banking;
2. To propose a conceptual model focusing on facilitators and inhibitors influencing the behavior intention of bankers.

Proposed Conceptual Model

Figure 1
Proposed Conceptual Model



In the above conceptual model, the unified theory of acceptance and the use of technology (UTAUT) were integrated with risk, perceived complexity, and technological anxiety to provide a comprehensive conceptual model that explains both the facilitators and inhibitors affecting the behavioral intention of bankers to use AI. This is one of the few studies wherein facilitators and inhibitors are studied together to understand the effect on dependent variable. i.e., behavioral intention to use AI in Indian banking. The independent variables are divided into two parts: facilitators. which assumes constructs have a positive relationship with dependent variables that indicate behavioral intention to use AI, and inhibitors, which assume constructs have a negative relationship with BI. There are facilitators and inhibitors impacting the behavioral intention of bankers to use artificial intelligence. Through this model authors have tried to understand which independent variables are affecting the dependent variable and how.

Setting of Hypotheses

In order to test the behavioral intention of bank employees towards the use of artificial intelligence technology in banking on the basis of six parameters: performance expectancy, effort expectancy, social influence, risk, perceived complexity, and technological anxiety. Hypotheses are tested on primary data collected from bank employees working in bank branches in Delhi / NCR. A questionnaire is a quick and efficient way to obtain information from a large number of respondents. The authors intended that the questionnaire be simple, and questions relate to artificial intelligence technology and the respondents' work. The model behavioral intention of bankers with regard to use of artificial intelligence technology in the workplace was based on six parameters: performance expectancy, effort expectancy, social influence, risk, technological anxiety, and perceived complexity. In order to test the hypotheses, the authors set the following hypothesis separately for each parameter:

Factors Influencing the Behavioral Intention of Bankers

Factor	Definition	Source
Performance expectancy	Levels that indicate the extent to which users believe that performance will increase using the system.	(Venkatesh, et al, 2003)
$H_{o1:}$ There is no significant association between performance expectancy and behavioral intention to use AI in banking $H_{11:}$ There is a significant association between performance expectancy and behavioral intention to use AI in banking		
Effort expectancy	It is defined as the level of ease in using the system	(Venkatesh, et al, 2003)
$H_{o2:}$ There is no significant association between effort expectancy and behavioral intention to use AI in banking $H_{12:}$ There is a significant association between effort expectancy and behavioral intention to use AI in banking		
Social influence	It shows the degree to which a user perceive that important others believe he or she should use the new technology.	(Venkatesh, et al, 2003)
$H_{o3:}$ There is no significant association between social influence and behavioral intention to use AI in banking $H_{13:}$ There is a significant association between social influence and behavioral intention to use AI		

Factors Inhibiting the Behavior Intention of Bankers

Factor	**Definition**	**Source**
Risk	User's perception of the uncertainty and negative consequences after engaging in new activity	(Im et al., 2007)
$H_{o4:}$ There is no significant association between risk and behavioral intention to use AI in banking $H_{14:}$ There is a significant association between risk and behavioral intention to use AI in banking		
Perceived complexity	It specifies how far an innovation is perceived to be complex or difficult to understand.	(Moore & Benbasat, 1991)
$H_{o6:}$ There is no significant association between perceived complexity and behavioral intention to use AI in banking $H_{16:}$ There is a significant association between perceived complexity and behavioral intention to use AI in banking		
Technological anxiety	It is a negative emotional response, such as fear or discomfort, when users think about using a new technology	(Hong, et al., 2012)
$H_{o6:}$ There is no significant association between technological anxiety and behavioral intention to use AI in banking $H_{16:}$ There is a significant association between technological anxiety and behavioral intention to use AI in banking		

In the conceptual model (Figure 1), the above-mentioned six factors have been considered as independent factors affecting the behavior intention of bankers (i.e., dependent variable). Behavioral intention is the level at which someone has planned to do or will not do something in the future source (Venkatesh, et al, 2003).

Research Methodology

Sample And Data Collection

Only three categories of commercial banks, namely private sector banks, public sector banks, and foreign banks, have been considered in the survey from Delhi/ NCR. The research survey form was circulated among these bank branches, and, finally, 108 complete responses were collected from bankers (clerks, officers, and executives) through the structured questionnaire method. The data collected was tabulated and analyzed for the purpose of giving detailed and precise information. A five-point Likert scale is used to assess the collected responses of the bank employees and behavioral intention of bankers (Likert, 1932). Analysis of the data was done after assigning the following scores: 1 -Strongly disagree; 2 – disagree; 3- neutral; 4- agree 5- strongly agree

Table 1
Demographic Profile

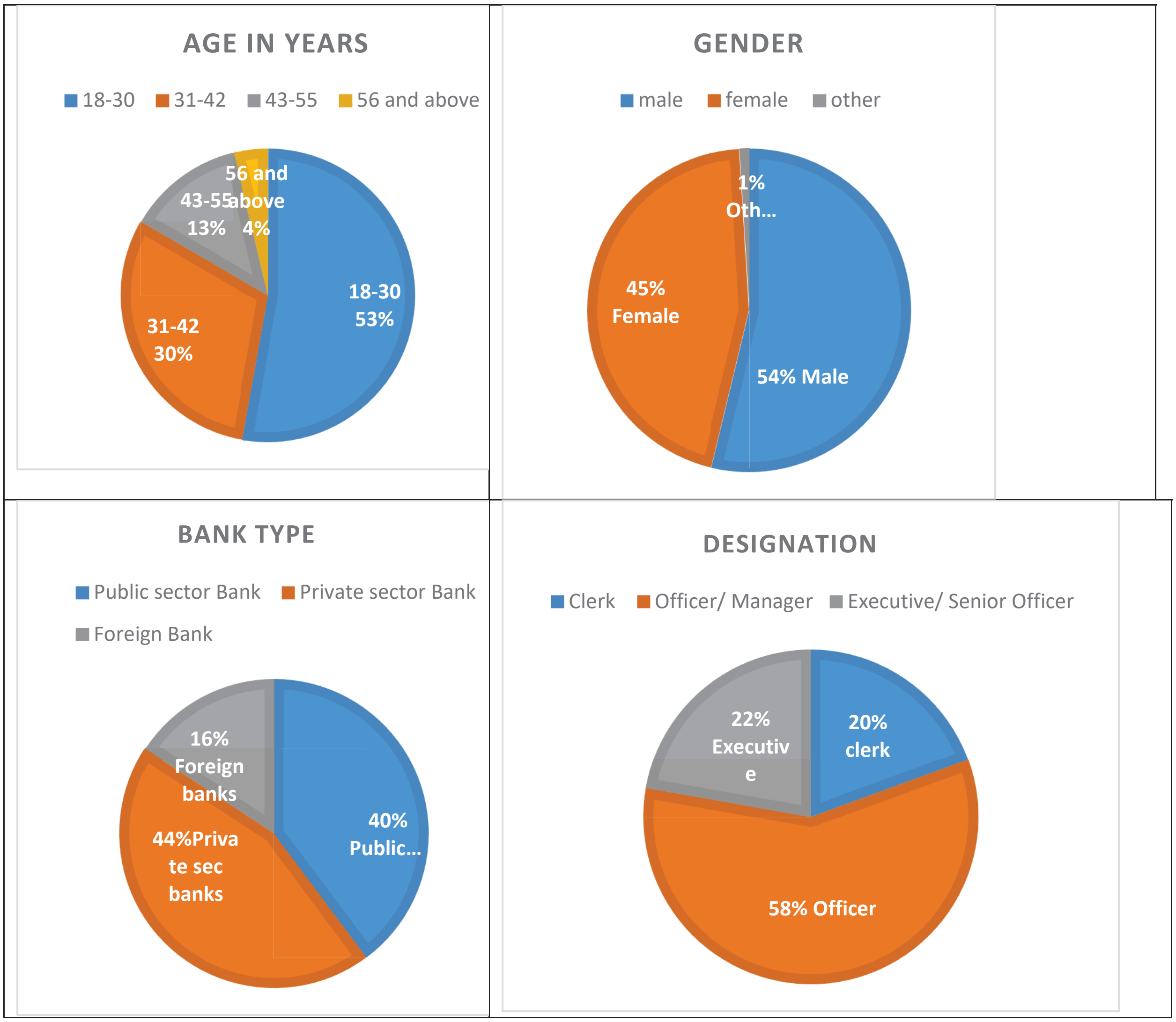
Demographic	Frequency	Percentage	Cummulative frequency
Gender			
Male	58	53.70%	53.70%
Female	49	45.37%	99.07%
Other	1	0.93%	100.00%
Age			
Z-30	57	52.78%	52.78%
31-42	33	30.56%	83.33%
43-55	14	12.96%	96.29%
56 and above	4	3.70%	100.00%
Bank type			
Public sector Bank	43	39.82%	39.82%
Private sector Bank	48	44.44%	84.25%
Foreign Bank	17	15.74%	100.00%
Designation			
Clerk	21	19.45%	19.45%
Officer/ Manager	63	58.33%	77.78%
Executive/ Senior Officer	24	22.22%	100.00%
Frequency of using AI			
Never	3	2.78%	2.78%
Rearely	4	3.70%	6.48%
Sometimes	22	21.30%	27.78%
Often	40	37.03%	64.81%
Always	38	35.19%	100.00%
Hours in which AI applications are used every week			
Less than 1 hour	12	11.11%	11.11%
1-5 hours	33	30.55%	41.66%
6-10 hours	22	20.37%	62.03%
11-15 hours	22	20.37%	82.40%
More than 15 hours	19	17.60%	100.00%

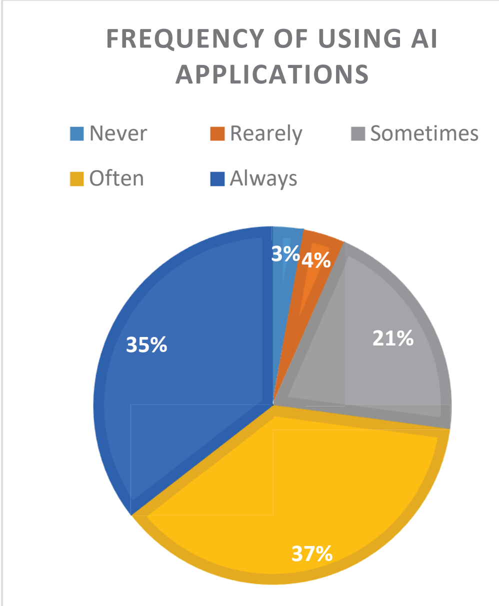
The quantitative results revealed that 53.70% of the respondents were male, 45.37% were female, and 0.93% belonged to other groups. The largest proportion (57%) of respondents by age group were those in the 18-30 years old category, followed by those in the 31-42 years category (30.56%), followed by those in the 43-55 years category (12.96%), and the remaining were respondents above the age of 56 (3.70%). The majority of surveyed respondents belonged to a private sector bank (44.44%), followed by public sector banks (39.82%), finally, followed by foreign sector banks (15.74%). On the basis of designation, 58.33% of respondents were officer/managers, 22.22% were executive/senior officers, and the remaining were clerks 19.45%.

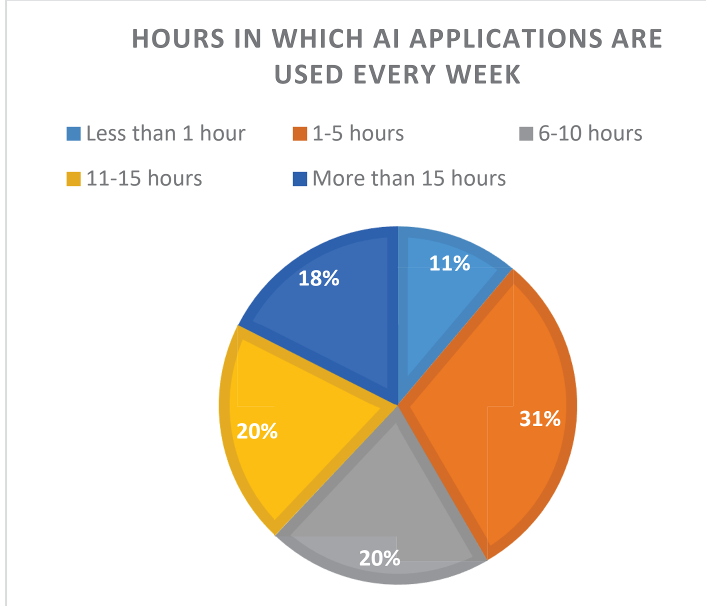
The survey also showed that 37.03% of AIU users often preferred using AI applications, while 35.19% of AI users always preferred using AI applications. Of the AI users, 21.3% sometimes preferred using AI applications, and 2.78% of AI users never used AI applications. The majority of respondents to the survey used AI applications every week for 1-5 hours (30.55%), followed by users who prefer using AI applications every week from 6-15 hours (20.37%), followed by users who prefer using AI applications every week more than 15 hours (17.60%), and 11.11% were users that prefer using AI applications every week for less than 1 hour.

Figure 2

Pie representation of Demographics







Data Analysis and Results

The random sampling method was adopted for the selection sample. After that, the snow- ball sampling method was used to obtain responses from bankers. To have a representative sample of the population, the equal representation of the age, gender, and geographical location was ensured. A total 150 questionnaires were sent through the Google Form link to individual bank employees in Delhi / NCR in India. A total of 108 responses were received and were found suitable for study. The response rate was 72%. The final sample of 108 bankers is now considered for data analysis.

Table 2
Reliability statistics

Variables	Cronbach's alpha	No. of items	Internal consistency
Performance expectancy	0.786	4	Acceptable
Effort expectancy	0.711	4	Acceptable
Social Influence	0.873	4	Good
Risk	0.908	4	Excellent
Perceived complexity	0.847	4	Good
Technological Anxiety	0.843	4	Good
Behavioral intention	0.851	4	Good

Cronbach's alpha measures internal consistency. It further assesses how closely related a set of items are with each other. It checks the inter item reliability of each variable. As reported in above Table 2, all the items show a relatively high degree of consistency. A reliability coefficient of 0.70 or higher is considered acceptable in most social science research (Hair et al., 2016).

Table 3
KMO and Bartlett's test Sphericity

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.733
Bartlett's Test of Sphericity	Approx. Chi-Square	1740.728
	Df	378
	Sig.	0.000

It was observed that the Kaiser-Meyer-Olkin measure of sampling adequacy, the KMO value, was 0.733, which was more than the recommended value of 0.6 for sample adequacy. Bartlett's test of sphericity was also significant at 0.000, which is below the p value <0001. The KMO statistic varies between 0 and 1 and a value ≥ 0.5 is acceptable (Kaiser, 1970). Bartlett's Test of Sphericity rejects the null hypothesis at a value lower than 0.05 significance level (Snedecor and Cochran, 1989).

Table 4
ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	174.277	6	29.046	6.729	.000[b]
	Residual	435.973	101	4.317		
	Total	610.250	107			

a. Dependent Variable: BI
b. Predictors: (Constant), TA, SI, RISK, EE, PC, PE

Analysis of variance (ANOVA) is constructed for determining whether three or more sample means were drawn from the population with equal means. It is used to check variation in responses between samples so that it can be ascertained if there exists considerable difference in behavior intention. The F test indicates that there is a significant difference in the mean responses given for samples collected. If the value of the F test is below 0.05, then there is evidence to reject the Ho in favor of Ha. The above model explains that the model so framed is acceptable and significant, as the value in significance column is below 0.05.

Exploratory Factor Analysis

Table 5

Total Variance Explained

Compo-nent	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.806	20.737	20.737	5.806	20.737	20.737	4.397	15.704	15.704
2	4.713	16.833	37.570	4.713	16.833	37.570	3.050	10.894	26.599
3	2.556	9.129	46.700	2.556	9.129	46.700	2.961	10.574	37.172
4	2.141	7.645	54.345	2.141	7.645	54.345	2.815	10.052	47.225
5	1.923	6.868	61.212	1.923	6.868	61.212	2.807	10.024	57.248
6	1.679	5.996	67.208	1.679	5.996	67.208	2.201	7.860	65.108
7	**1.180**	**4.213**	**71.422**	**1.180**	**4.213**	**71.422**	**1.768**	**6.314**	**71.422**
8	.852	3.045	74.467						
9	.724	2.587	77.053						

Factor analysis is used to understand the range of factors that have a strong influence on the behavioral intention of bankers to use AI technology. In the study, there are seven variables considered: performance expectancy, effort expectancy, and social influence are considered as influencers towards behavioral intention to use AI. Risk, technological anxiety, and perceived complexity are considered inhibitors towards behavioral intention to use AI in banking. Behavioral intention to use AI is considered a dependent variable. Influencers and inhibitors jointly explain 71.422% of variance in the behavior intention to use. The initial Eigen value of the seven factors is greater than 1, and the factor loading is more than 0.5. Hence, Table 5 shows how these seven factors explain the overall variance. The total cumulative percentage of the extracted factors is more than 50%, i.e., 71.422%, which is good for the sample size of 108 respondents. Eigen values have been taken together with the principal component, respectively.

Table 6
Rotated Component Matrix Through Varimax Method

	Component						
	1	2	3	4	5	6	7
PE1			.776				
PE2			.748				
PE3			.732				
PE4			.766				
PE5			.507				
EE1							.871
EE2							.842
S2						.628	
S4						.849	
S5						.773	
R1	.765						
R2	.864						
R3	.847						
R4	.768						
R5	.827						
R6	.725						
PC1				.748			
PC2				.794			
PC3				.846			
PC4				.774			
TA1					.841		
TA2					.770		
TA3					.850		
TA4					.797		
B1		.663					
B2		.878					
B3		.870					
B4		.898					

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 6 iterations.

Figure 3

Scree Plot and regression line

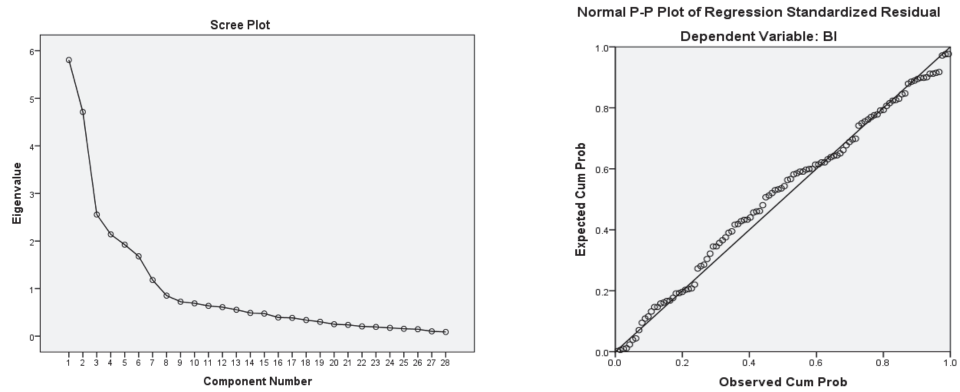


Table 7

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.680[a]	.462	.430	2.947	.462	14.458	6	101	.000	1.985

a. Predictors: (Constant), Perceived complexity, Performance Expectancy, Technological Anxiety, Risk, Social Influence, Effort expectancy
b. Dependent Variable: Behavioral Intention

The model framed in Figure no. 1 is run through SPSS, and the results show that the model is acceptable and significant, as the value of Sig. F Change is below 0.05. The model framed is acceptable if f changes value < 0.05. The value of R square is 46.2%, which means 46.2% of the change in behavioral intention of bankers to use AI is explained by six independent factors considered in the research study. The Durbin Watson statistic is a test for auto correlation in a regression model. The value ranges from 0 to 4. A value equal or near 2 indicates no auto correlation. A value below 2 indicates a positive autocorrelation, whereas a value above 2 indicates a negative autocorrelation. In this case, the Durbin Watson statistic value is 1.985, which is very near to 2, which shows zero autocorrelation between variables.

Table 8

Multiple Regression

Coefficients

Hypothesis relationship		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	RESULTS
		B	Std. Error	Beta			H_a
	(Constant)	8.202	2.598		3.157	.002	3.049
	PE → BI	.125	.128	.102	.976	.331	Rejected
	EE → BI	.134	.106	.120	1.258	.211	Rejected
	SI → BI	.272	.090	.306	3.015	**.003**	**Accepted**
	RISK → BI	-.212	.066	-.294	-3.209	**.002**	**Accepted**
	PC → BI	.101	.073	.126	1.375	.172	Rejected
	TA → BI	.087	.066	.112	1.316	.191	Rejected

a. Dependent Variable: Behavior Intention

The survey data obtained was analyzed using both descriptive and quantitative techniques. Descriptive statistics explain the use of respondent profile, whereas quantitative techniques shall involve various statistical tools, namely reliability, exploratory factor analysis, ANOVA, and multiple regression analysis. The data was evaluated using Microsoft Excel and specialized software: The Statistical Package for Social Science (SPSS). After satisfactory results in reliability and validity, data was run on multiple regression analysis and exploratory factor analysis.

Multiple regression analyzes the relationship between constructs with multiple measurement items. This study made an attempt to describe the behavioral intention of bankers to use AI technology by extending the unified technology acceptance and use of technology (UTAUT) with risk, perceived complexity, and technological anxiety. The above explains that Hypotheses 1, 2, 5, and 6 are rejected, as relationships between the variables are weak (ie., $p>0.05$). Hypotheses 3 and 4 are accepted because there is strong association between variables ($p<0.05$) Social influence and risk have strongly affected the behavior intention of the bankers to use artificial intelligence technology.

Discussion and Conclusion

As the number of bank transactions is growing rapidly every day, bank customers' expectations of their bank have increased. Customers demand real-time transaction status, management of portfolios with expert suggestions, early fraud detection, personalized services, and quick processing of their files. Commercial banks are getting stiff competition from fintech players. Fintech is canvassing the customer base on the basis of emerging technologies, like machine learning, artificial intelligence, and the like. As a result, it is imperative for any bank to provide the best services leading to customer engagement. Emerging technologies like artificial intelligence aids bankers in handling credit portfolios, providing them real-time updates, algorithm-based suggestions on portfolio management, early fraud detection warnings, and many more applications.

The findings of the study confirmed that out of three facilitators, namely performance expectancy, effort expectancy, and social influence, social influence plays an important role and also poses a direct effect on the behavioral intention of bankers to use AI. The social influence beta is0.306, and the p value is 0.003 ($p<0.05$). The findings further confirmed that out of three inhibitors, namely risk, perceived complexity, and technological anxiety, risk plays an important role and poses a direct effect on behavioral intention of bankers to use AI in banking. The risk beta is -0.294, and the p value is 0.002 ($p<0.05$). In other words, results show that other people who are important to users (bankers) influences are influenced in their behavior towards using the latest technologies, like AI. On the other hand, risk is the inhibiting factor that is playing a significant role in stopping a banker from using new technology; risk is, basically, a chance of uncertainty or adverse consequences. The risk bankers take can be reduced by providing them proper training and user manuals whenever they feel anxious or confused. This result gives detailed explanation of Indian bankers' slow acceptance of artificial intelligence technologies.

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