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AN EXPLORATORY STUDY OF EMPLOYEES' ATTITUDES TOWARD CUTTING-EDGE TECHNOLOGIES

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ABSTRACT
The use of artificial intelligence (AI) in business is common and useful nowadays. Artificial intelligence is all about simulating human behaviour while carrying out jobs more accurately, quickly, and efficiently. Information that requires minimal to no human input can likewise be produced using algorithms. It can be stated that ai - powered implementation has an impact on the efficiency of the banking industry because the adoption of efficient artificial intelligence-related practises in both public and private sector banks enables an increase in workforce productivity and organisational performance. This study employs both descriptive and exploratory research designs. For this study's conclusion, SEM and confirmatory factor analysis were used. The use of AI, time demands technology, and advancement and revamping are all having a significant impact on bank employees' attitudes. Due to their favourable attitude toward AI, employees support its acceptance and application in banking. Despite the difficulties it brings, technology adoption in banking has always been seen as a benefit for staff members.
Keywords: Artificial Intelligence, Time demand technology, Advancement and Revamping, Employee Attitude.

INTRODUCTION
In the digitalization and transformation of contemporary organisations, artificial intelligence (AI) represents a significant advancement. In a nutshell, it refers to the ability of computers to

learn and apply knowledge independently of programmers. AI has enormous promise for significant efficiency gains and potential revenue growth, much like earlier examples of information technology (IT) application in the financial services industry. However, there hasn't been much use of AI in banking thus far. AI is currently being tested for the real-time detection and prevention of fraud in know-your-customer (KYC) procedures and online banking. Robo-advisors are also developing into actual AI solutions over time. In the future, legislative restrictions on data privacy and worries about cybersecurity may make it difficult to deploy AI in banking. Additionally, some of the efficiency gains of AI may be offset by the banking industry's strict regulations. It is important to recognise the possible impact AI could have on bank profitability. Empirically, AI significantly improves the return on assets for European banks (ROA). AI technologies have the potential to structurally lower costs in the banking industry by raising labour productivity. Therefore, combating continuously low profitability and maintaining competitiveness depend heavily on the quick adoption of AI technology.

The rapid advancement of internet, computer hardware, and software technologies has permanently altered our communities. Today, it is challenging to think of a business agent without computers, the internet, or mobile devices. The speed at which IT is developing provides excellent opportunity to grow the customer base, launch new products or improve existing ones, and boost productivity in a short amount of time. However, businesses may quickly be left behind by developments if they miss the current IT wave. The development in AI stands out among the numerous IT innovations of recent years. In a nutshell, artificial intelligence (AI) refers to machines that have cognitive abilities comparable to those of humans. This might lead to significant efficiency advantages for businesses and their clients. The financial industry was among the first to experiment with AI technologies, in part because of the technology's potential to boost profitability. Therefore, it is crucial to look more closely at the potential contribution of AI to the digital transformation of banks.

The majority of a bank's business operations, including traditional deposit taking and lending as well as investment banking and asset management, depend on data. Therefore, banks have a lot of chances to increase speed, accuracy, and efficiency through autonomous data handling without human intervention. Four major categories can be used to classify potential AI banking applications: Front office apps with a focus on the customer, back office applications with a focus on operations, trading and portfolio management and regulatory compliance. The majority of banks are still testing out AI technologies rather than fully integrating them into their operations, at least for the time being.

AI solutions with a focus on customers and operations appear to be being explored more thoroughly than others, Online banking fraud detection and prevention using AI are now being tested. In fact, the high rise of online and mobile payments has made credit card fraud one of the most pervasive types of cybercrime in recent years. AI algorithms use real-time plausibility checks on client credit card transactions and comparisons of new transactions to historical amounts and locations to spot fraudulent behaviour. If it detects threats, AI will halt transactions. Additionally, AI is being tested in KYC procedures to confirm clients' identities. AI programmes scan client documents and assess the accuracy of the data by contrasting it with data from the internet. Inconsistencies found by AI algorithms raise a red flag, prompting bank workers to conduct a more thorough KYC check.

Our lives have changed significantly as a result of AI, and we are rapidly moving into a "Machine Age." The world's computer communications networks can be accessed through AI. The growth of artificial intelligence has enabled new technical developments. The results of the AI Revolution are available in more and complete detail in modern banking. Modern banks must be knowledgeable about AI and ensure that their clients' and workers' awareness of AI in banking. The focus of the digital transformation of banking institutions with a large digital economy must be on AI. In the world of computer technology, machine learning and knowledge are the foundations of AI-based banking.

As they say, "Necessity is the mother of invention." The development of pervasive technology has altered how people think and act across time. The shift in public perception from cable networks to internet networks has facilitated the widespread deployment of AI technologies. Traditional banking and financial services firms are working with Fintech enterprises to provide their customers cutting-edge services.

REVIEW OF LITERATURE

Lee and Chen (2022) demonstrated how the use of mobile applications has revolutionised the traditional banking industry. Customers' propensity to use mobile banking apps appears to be positively impacted by intelligence and anthropomorphism. Non-probability sampling was used to collect the data, and partial least squares was used to analyse it. These results advance the acceptance theory for AI-based mobile apps and offer suggestions for banks looking to employ AI to retain clients. **Payne et al., (2021)** uses five roots to examine the value-in-use attitudes of automation mobile banking apps: standard perceived of current banks' service provision, advantages of service configuration delivery, Perceptions of overall data protection, M-banking security, and how AI services are provided. Mobile banking technologies, especially those that deal with collecting, storing, and analysing customer data, are also pushing banks to include AI into their online and mobile platforms. Chatbots that interact with customers verbally or via text messaging are among the AI mobile banking (AIMB) services, as are tools for spotting fraud and providing individualised financial guidance. **Sharma and Padhi (2020)** reportedly improves the way the sector looks, makes processes more comfortable, and enables problems to be appropriately stated, allowing human expertise and machine and deep learning algorithms to more accurately associate human choice. They identified two variables: the transition from tech savvy individuals to technologically literate people and the synthesis of many technical aspects to expand technical boundaries. Exploratory research was employed along with extensive literature studies to conduct this study. The GC (Great Convergence) framework for intelligent process automation is used to analyse data from primary sources, which aids in comprehending the essential component of artificial intelligence. **Sreeju (2020)** focused on how to move toward a cashless society by combining banking services with cutting-edge technology to help with ease, efficiency, and transparency. These aspects benefit consumers, and transformation is crucial to the modern economy as it creates new markets. Information is gathered through secondary sources. Websites, research papers, media, information technology, and other sources were used to get this data. The study is descriptive, and there has been some exploratory research. They discovered that by using financial technologies like online banking, mobile banking, and QR codes, opportunities can be taken advantage of and obstacles can be overcome. **Shanthi and Pavithra (2020)** conducted a survey that showed that clients are open to using chatbots. After applying AI, technology is gradually becoming smarter and appreciating new industries utilising this technology. Data were gathered using primary and secondary foundations, and the study was only conducted in Chennai. The chosen bank was given the questionnaire, and a sample size of 50 was chosen for analysis. Websites and online publications collect secondary data. To achieve their goals, they applied the chi-square, percentage, and Friedman rank tests. **Bhatti (2019)** looked at the state of chatbots at the moment and found that they are user-friendly and simple to use, giving customers favourable impressions of the technology. Surveys have been used to gather data. A pilot study, descriptive research, and the purposive sample approach were used to conduct the analytical investigation. The survey was conducted just in Kenyan banks and insurance companies to see how aware their clients are of chatbots and AI technology. They set up chatbots to provide prompt answers to their queries and worries.

RESEARCH METHODOLOGY

When gathering information from workers of public and commercial banks, a convenient sampling technique was used. The researcher then took a sample of the respondents—300 employees of the chosen banks—after further segmenting the population into categories based on gender, bank categories, geographic region, etc. In Southern Rajasthan, the researcher has chosen 6 districts for data collection: Udaipur, Banswara, Chittorgarh, Pratapgarh, Dungarpur, and Rajsamand. From these 6 districts, 10 banks have been chosen as the main geographic region for data collection. From the aforementioned six districts of Southern Rajasthan, the researcher has chosen five public banks—SBI Bank, PNB Bank, Bank of Baroda, Canara Bank, and Union Bank of India—and five private banks—HDFC Bank, ICICI Bank, Axis Bank, Kotak Mahindra Bank, and IndusInd Bank.

The facts acquired from both primary and secondary data sources will be used to support the conceptual framework of the study. Secondary resources were acquired from annual reports of specific banks, banking industry publications, and a number of pertinent periodicals and magazines. Secondary data will also be gathered from the Faculty of Management Studies Library and the Central Library of MLS University, Udaipur. The respondents were chosen from five public and five private sector banks in the six Southern Rajasthan districts that were listed. The survey has been done through self-structured questionnaire.

DATA ANALYSIS AND INTERPRETATION

The study's sample size was 300 employees, 156 of whom were men and 144 of whom were women. 104 responses were between the ages of 18 and 25, 55 were between the ages of 26 and 30, 39 were between the ages of 31 and 40, 35 were between the ages of 41 and 50, 64 were between the ages of 51 and 60, and 3 were over the age of 60. There were 115 married, 160 single, 21 widowed, and 4 divorced respondents. As far as employee designations go, 65 respondents are top managers, 71 are quality control managers, 55 are line managers, 36 are executives, 5 are HR managers, and 16 are branch managers. 30 respondents reported monthly incomes of less than 10K, 25 respondents are from 10K-20K, 42 respondents are from 20K-30K and 30K to 40K, 120 respondents are from 40K to 50K and 41 respondents are 40K and above.

When determining which factors are accurate and valuable, there are a number of cutting-edge technology sources that can have an impact on employees' attitudes and difficulties after the AI revolution. Additionally, because these many variables have been condensed into a few key dimensions, it is clear that these particular elements are directly influencing how employees feel about adopting cutting-edge technology.

To evaluate how the set of factors that have been observed interact. Multivariate factor analysis is employed to extract variables and ascertain how closely selected components are associated. Prior to using factor analysis on a particular data set, it is critical to ascertain whether it can be employed. The Kaiser-Meyer-Olkin sample adequacy measure, Bartlett's test of sphericity, and a correlation matrix for the descriptor variables are used to determine whether the link between the variables is strong enough to apply factor analysis. Consequently, the researcher used factor analysis as follows:

Table 1- Descriptive statistics table

Descriptive Statistics			
	Mean	Std. Deviation	Analysis N
B22i	3.62	.934	300
B22ii	3.70	.875	300
B22iii	3.69	.869	300
B22iv	3.68	.857	300
B22v	3.63	.870	300
B22vi	3.39	.829	300
B22vii	3.80	.915	300
B22viii	3.67	.831	300
B22ix	3.55	.793	300
B22x	3.56	.957	300
B22xi	3.63	.922	300
B22xii	3.65	.889	300
B22xiii	3.97	.823	300
B22xiv	3.92	.802	300
B3i	3.94	.797	300
B3ii	3.90	.772	300
B3iii	3.98	.805	300
B3iv	4.00	.799	300
B3v	3.99	.838	300
B3vi	3.62	.894	300
B3vii	3.62	.905	300
B3viii	3.66	.876	300
B3ix	3.77	.825	300
B3x	3.57	.963	300

The descriptive statistics for the claims under "New technology is significantly influencing the attitude of banking staff" are shown in the above table. The information above, including the mean value, standard deviation, and number of respondents, shows how variable each item's score really. According to the data, variable B3iv has the greatest mean.

Table 2 - KMO and Bartlett's: Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.924
Bartlett's Test of Sphericity	Approx. Chi-Square	6860.811
	df	276
	Sig.	.000

On the basis of the underlying factors, a typical variance is shown in the above table. This sample size makes it possible to perform a factor analysis. If factor analysis is appropriate for the data, a value in the range of 0.5 to 1 is displayed. This statistic's low value of 0.5 means that no factors can be applied to the data. The factor analysis is appropriate for the data, according to the KMO statistic calculated above, which is 0.924. Bartlett's test outcomes are also displayed; this statistic is used to choose the right factor analysis model. The Bartlett's test determines whether the population's correlation matrix is an identity matrix. The result of a Chi-square test with 276 degrees of freedom is 6860.811, which is significant at the 1% level [p 0.01]. As a result, both the KMO and Bartlett tests confirm that factor analysis is adequate.

Table 3- Communalities table

Communalities		
	Initial	Extraction
B22i	1.000	.694
B22ii	1.000	.754
B22iii	1.000	.829
B22iv	1.000	.824
B22v	1.000	.660
B22vi	1.000	.563
B22vii	1.000	.623
B22viii	1.000	.626
B22ix	1.000	.854
B22x	1.000	.715
B22xi	1.000	.855
B22xii	1.000	.829
B22xiii	1.000	.807
B22xiv	1.000	.849
B3i	1.000	.848
B3ii	1.000	.872
B3iii	1.000	.824
B3iv	1.000	.762
B3v	1.000	.760
B3vi	1.000	.729
B3vii	1.000	.820
B3viii	1.000	.801
B3ix	1.000	.821
B3x	1.000	.756

Extraction Method: Principal Component Analysis.

The amount of variance that a variable shares with other variables is referred to as its communality. The original communalities and extracted communalities for each variable in the factor analysis are displayed in the table above. The initial communality value for all variables is one since SPSS by default gives all variables a value of one, as seen in the table above. Using the extracted communalities, it is possible to calculate each variable's variance. If a variable is inappropriate for the factor solution, it can be essential to remove it from the factor analysis if its communality value is less than 0.5.

The main component approach is one of the most used ways to reduce data in factor analysis. Finding the fewest possible components that account for the data's greatest variance or variability is the main goal of factor analysis. To choose how many factors to keep, factor analysis can be done in a number of different ways. Here, factors were extracted using an eigenvalue-based strategy. The eigenvalue approach suggests taking into account factors with more than one eigenvalue. Four components were included in our model since their eigenvalues were greater than one. To rotate the model, we employed varimax orthogonal rotation.

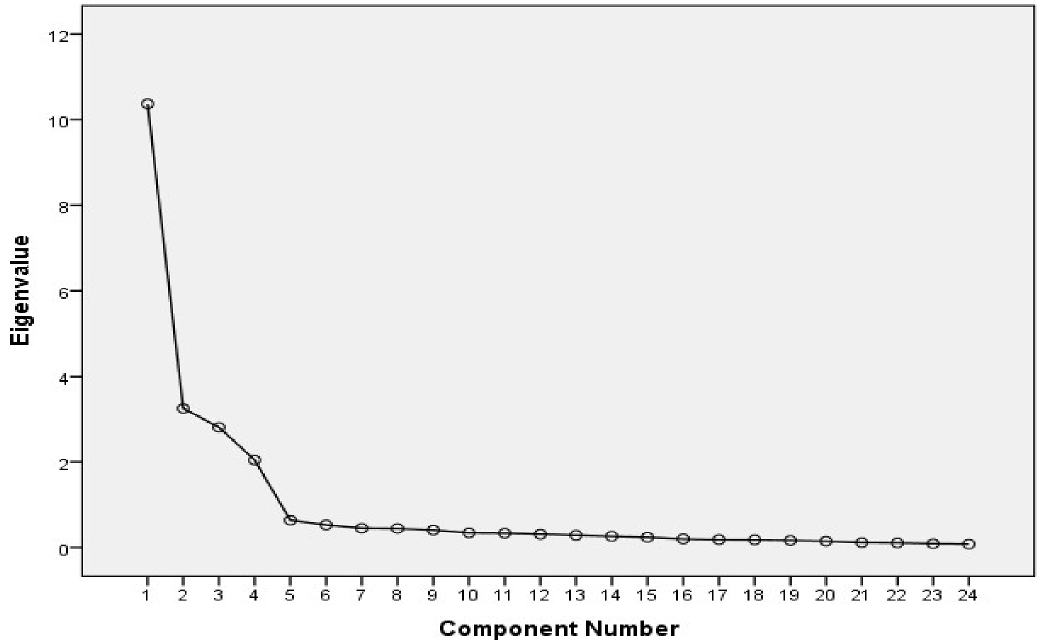
Table 4- Variance Explained Table

Total Variance Explained									
Component	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	10.37	43.208	43.208	10.37	43.208	43.208	5.503	22.928	22.928
2	3.252	13.548	56.756	3.252	13.548	56.756	5.148	21.449	44.377
3	2.812	11.716	68.472	2.812	11.716	68.472	4.009	16.705	61.082
4	2.044	8.518	76.991	2.044	8.518	76.991	3.818	15.908	76.991
5	0.638	2.66	79.651						
6	0.527	2.196	81.847						
7	0.449	1.87	83.717						
8	0.444	1.849	85.566						
9	0.406	1.69	87.256						

10	0.343	1.428	88.683						
11	0.336	1.398	90.081						
12	0.311	1.298	91.379						
13	0.288	1.199	92.578						
14	0.262	1.091	93.669						
15	0.239	0.997	94.666						
16	0.2	0.835	95.501						
17	0.185	0.77	96.271						
18	0.18	0.75	97.021						
19	0.165	0.687	97.707						
20	0.15	0.623	98.33						
21	0.118	0.49	98.821						
22	0.11	0.46	99.281						
23	0.091	0.38	99.661						
24	0.081	0.339	100						
Extraction Method: Principal Component Analysis.									

Four latent construct factors were found using principal component analysis. The amount of variance that can be explained by the first factor is increased by combining the original variables in a linear way. Four components were identified by principal component analysis as accounting for 76.991 percent of the total variation. When performing a factor analysis, the number of components shown by the plot is kept in consideration. For the purpose of factor extraction, four components with steep slopes were examined.

Graph 1- Scree Plot Graph



The rotation of factors causes a link between variables and factors. The variables and components that make up the factor are described by a factor loading. Only items having a strong link to a factor are included in a factor loading in this table. A factor is what it is because the components that make it up stand for characteristics. The factors that were extracted are as follows: Employee Attitude, Time Demand Technology, Advancement and Revamping, and AI Adoption are the four Fs.

Table 5- Rotated Components Matrix

Rotated Component Matrix[a]				
	Component			
	1	2	3	4
B3i- Change in the Workplace	.861			
B3ii- Insufficient management assistance	.860			
B3iii- Lack of technical expertise	.855			
B22xiv- Working with technology makes me uneasy	.831			
B22xiii- Adoption of new technologies makes me feel better	.817			
B3v- Working with New Technology Is Difficult	.799			
B3iv- Greater workload	.793			
B22xi- I am learning new abilities as a result of the bank using AI		.886		
B22ix- I believe that training is necessary for a deeper grasp of AI methods		.881		
B22xii- After working for an AI-implemented bank, I feel proud		.867		
B22x- After implementing AI, I am feeling pressured		.813		
B22viii- I appreciate how quickly services are processed now that AI is being used		.742		

B22vii- After AI adoption and deployment in banks, I am satisfied		.725		
B22vi- I was pleased with the management's explanation of the advantages of AI		.694		
B3vii- Role and responsibility modification			.868	
B3ix- Job Uncertainty			.859	
B3viii-Aalteration of pay scale			.837	
B3x- Revised the HR policies			.834	
B3vi- Method Change			.798	
B22iii- When I learned about the introduction of AI, I was terrified for the future				.892
B22iv- I believed that implementing AI was the best method to boost the performance of banks				.881
B22ii- I received accurate information regarding AI and its applications				.858
B22i- I was able to comprehend the motivation behind my bank's deployment of AI				.823
B22v- Due to the complexity of the most recent technologies, I opposed the deployment of AI				.794
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.[a] a.Rotation converged in 5 iterations.				

Table 6- Cronbach's Alpha Table

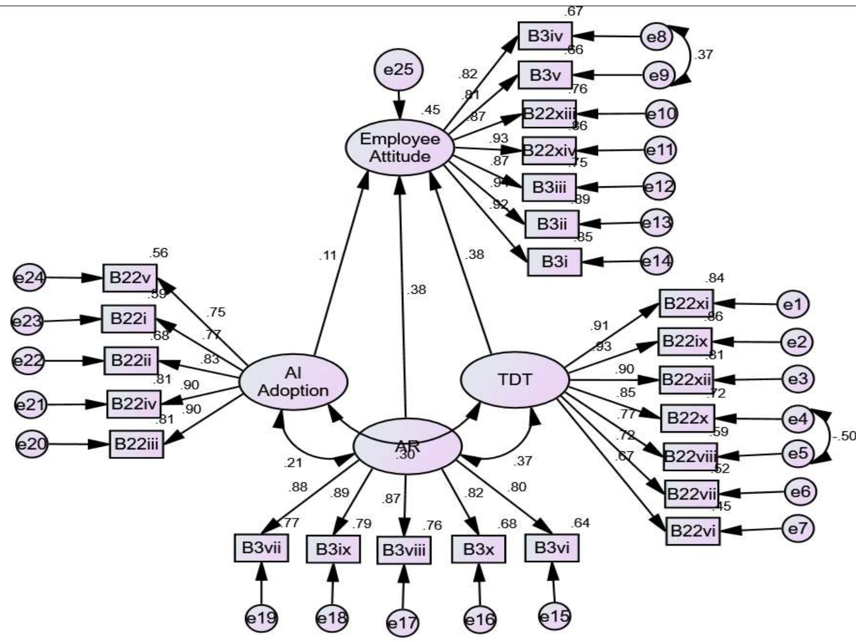
Factors	**Variables**	**Cronbach's alpha**	**Correlated Item-total Correlation**	**Cronbach's alpha if Item deleted**	**F (sig.)**
Employee Attitude	B3i	.962	.884	.954	3 (0.005)
	B3ii		.905	.953	
	B3iii		.868	.955	
	B22xiv		.887	.954	
	B22xiii		.858	.956	
	B3v		.824	.959	
	B3iv		.830	.958	
	B22xi		.881	.913	
	B22ix		.885	.915	
	B22xii		.862	.915	
	B22x		.769	.925	

Time Demand Technology	B22viii	.933	.715	.929	18 (0.000)
	B22vii		.716	.929	
	B22vi		.681	.932	
Advancement and Revamping	B3vii	.929	.844	.907	7 (0.000)
	B3ix		.847	.908	
	B3viii		.827	.911	
	B3x		.791	.919	
	B3vi		.770	.921	
AI Adoption	B22iii	.916	.849	.883	1 (0.000)
	B22iv		.843	.885	
	B22ii		.786	.896	
	B22i		.737	.907	
	B22v		.711	.911	

In the table above, the cronbach's alpha for all factors is higher than 0.07, and the corrected item-total correlation for each item is higher than 0.03. Additionally, it demonstrates that if an item is eliminated, the cronbach's alpha of the factor is lower than the significant value of the F test for all factors. Therefore, it suggests that using Cronbach's Alpha with a confidence level lower than 0.05 is suitable. It is trustworthy enough to merit additional investigation: Investigate the relationships between the components using SEM.

The link between the variables is shown using a structural equation model (SEM) in this section. A SEM model combines multiple regression and factor analysis. Confirmatory factor analysis (CFA), a part of structural equation modelling (SEM), aids in determining which variables and factors are appropriate for the structural model. The dependent variable for the second component, known as multiple regression, is employee attitude, and the regression weights between the independent variables Time Demand Technology, Employee Attitude, and AI Adoption are established. Here are the SEM results for AMOS;

Graph 2- SEM Model of Time Demand Technology, Employee Attitude, and AI Adoption on Employee Attitude



Notes: There are numbers above the arrows: Numbers in front of the objects representing estimates of the factor loadings and regression weights: Estimation errors for the variances e1, e2, and en. The outcome suggests that the model fits the data adequately. the probability level is.000, the chi-square is 500.892, and there are 244 degrees of freedom.

Here, the values for CMIN/df are 2.053, GFI for the default model is 0.980, CFI for the default model is 0.962, AGFI for the default model is 0.952, and RMSEA for the default model is 0.040, indicating that the sample data and hypothetical model are a good fit. The fit indices show a high value in this case, indicating a simpler model. As a result, the default model is accepted here.

Table 7- The impact of Advancement and Revamping, Time demand technology and AI adoption on employee attitude

The Impact			The Regression Index
Employee Attitude	<---	Advancement and Revamping	.383
Employee Attitude	<---	Time Demand Technology	.378
Employee Attitude	<---	AI Adoption	.108

The results of the positive and negative correlation between the dependent and independent variables are shown in the above table. As a result of the positive association between the components, advancement and revamping, time demand technology, and adoption of artificial intelligence all have a favourable effect on employee attitude. In a nutshell, we can state that modern technology is affecting bank employees' attitudes since they are curious to learn about cutting-edge technology and its advantages and disadvantages. Employees who use cutting-edge technology report that banks perform better, services are processed quickly, repetitive work is reduced, and data can be easily retrieved. However, they also report that using the newest technology is challenging, that their jobs are insecure, and that they lack technical knowledge.

Table 8: Interpretation of SEM Model

Parameter	Meaning	Standards	Values in analysis	Results
CMIN/DF	Chi-square divided by Degree of Freedom	≥ 3 = Acceptable fit	2.053	Acceptable Fit
		≤ 5 = Reasonable fit		
GFI	Goodness of Fit Index	1 = perfect fit	0.980	Excellent Fit
		≥ 0.95 = Excellent fit		
AGFI	Adjusted Goodness of Fit Index	≥ 0.9 = Acceptable fit	0.952	Acceptable Fit
CFI	Comparative Fit Index	1 = perfect fit ≥ 0.95 =	0.962	Excellent Fit
		Excellent fit ≥ .90 =		
		Acceptable fit		
RMSEA	Root Mean Square Error of Approximation	≤ 0.05 = Reasonable fit	0.040	Reasonable Fit

The following hypothesis is constructed to determine whether advancement and revamping, time demand technology, and adoption of AI are significantly impacting or not the mindset of banking staff;

H_{01}: There is no significant impact of Advancement and Revamping on bank employees' attitudes.

H_{01a}: There is no significant impact of Time Demand Technology on bank employees' attitude.

H_{01b}: There is no significant impact of AI Adoption on bank employees' attitude.

H_{A1}: There is no significant impact of Advancement and Revamping on bank employees' attitude.

H_{A1a}: There is no significant impact of Time Demand Technology on bank employees' attitude.

H_{A1b}: There is no significant impact of AI Adoption on bank employees' attitude.

Table 9- Regression weight (Default Model)

	Estimate	S.E.	C.R.	P
Employee Attitude <--- Advancement and Revamping	.349	.051	6.907	***
Employee Attitude <--- Time Demand Technology	.293	.042	6.972	***
Employee Attitude <--- AI Adoption	.090	.041	2.174	.030

The regression test results used to verify the proposed hypothesis are shown in the above table. According to the data, the null hypothesis is rejected if the p-value is less than 0.05, and the alternate hypothesis is rejected if it is greater than 0.05. Since the significance value of each construct latent factor in this situation is less than 0.05, the null hypothesis is rejected and the alternative hypothesis is accepted. In summary, advancement and revamping, time demand technology, and adoption of AI are all having a substantial impact on employees' attitudes and are positively correlated with attitudes among bank employees. Due to their favourable attitude toward AI, employees support its acceptance and application in banking. Despite the difficulties it brings, technology adoption in banking has always been seen as a benefit for staff members.

CONCLUSION

The banking sector will be impacted over the long run by an increase in AI usage. Legacy data systems might or might not function today, but they are not likely to function in the future. Banks are taking advantage of technological advancements since they are aware of them. AI has the potential to significantly change banking in ways that could affect the sector's long-term competitive advantages. Banks must maintain their current route in order to gain from AI in the future, which for some may be trickier than anticipated. As a result of the positive association between the components, advancement and revamping, time demand technology, and adoption of artificial intelligence all have a favourable impact on employee attitude. In a nutshell, we can state that modern technology is affecting bank employees' attitudes since they are curious to learn about cutting-edge technology and its advantages and disadvantages. Employees who use cutting-edge technology report that banks perform better, services are processed quickly, repetitive work is reduced, and data can be easily retrieved. However, they also report that using the newest technology is challenging, that their jobs are insecure, and that they lack technical knowledge. Therefore, the attitudes of employees are positively impacted by all of these factors.

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