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PRIORITISATION OF FACTORS FOR ARTIFICIAL INTELLIGENCE-BASED TECHNOLOGY ADOPTION BY BANKING CUSTOMERS IN INDIA: EVIDENCE USING THE DEMATEL APPROACH

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Abstract

Artificial Intelligence (AI) is a concept of recent origin and is accepted for banking activities such as customer service, detection of fraudulent activities, and suspicious transactions. For the successful implementation of AI in the Indian context, a deep understanding is required in terms of its need and importance compared to the traditional banking system. To date, this outlook of AI has been less focused by industry practitioners and experts for the smooth flow of operational procedures in banks for developing countries, for example, India. This study aims to unearth factors and establish a relationship among the identified factors through the decision-making trial and evaluation laboratory (DEMATEL) approach to categorize the factors and frame the cause-and-effect relationships. Fifteen factors are identified through a literature review of existing studies, and ten experts were solicited to express their outlook on this subject within a period of six months. The result indicated that 'Transparency of information,' 'Perceived security of AI-based technology,' 'Social influence on customer,' 'Government regulation of AI in banks,' 'Awareness level of AI,' 'Efficiency of AI system,' 'Technical requirement,' and 'Cost of AI-based technology' were causative factors that support customer acceptance and penetration of AI in banks. The study presents a unique approach to customer acceptability towards AI in banks in developing countries using the DEMATEL technique. This study also discusses the possible area for the adaption of AI in Indian banks. The findings will support policymakers and practitioners in executing AI-based technologies in the banking sector in emerging nations.

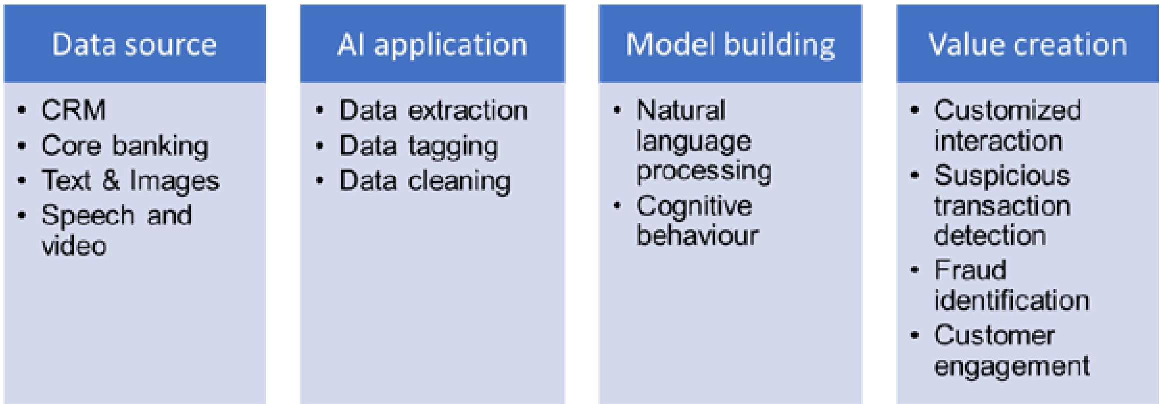
Keywords: DEMATEL; bank customers; artificial intelligence; Customer adaptation; India

1. Introduction

In today's world, Artificial Intelligence (AI) is considered one of the most promising technologies for customer service that incorporates algorithms, language, machine learning, etc (Wang et al., 2021; Rodrigues et al., 2022). AI tries to mimic human behaviour and intelligence to learn, think, and act similarly to gain insights about individuals' perceptions and predict future actions (Yadav, 2021). In the future, AI technology will be commercialized in other sectors, such as E-commerce, healthcare, supply chain, and disaster management (Singh and Srivastava, 2018). The AI system incorporates the Natural language of humans for understanding and generating responses for customer interaction in banks (Buchanan and Wright, 2021). Integration of customer services with AI technology would benefit the banking sector, where the customer database is extensive, and analysis of these data is required precisely and accurately. The requirement of services for financial investment for customers and improving those areas for customer retention can be fulfilled by AI very efficiently (Tao et al., 2021).

Additionally, if the customer is satisfied with the response rate and the queries are resolved satisfactorily, then the trust factor is multiplied. Adopting these AI-based technologies could reduce the cost of accessibility of credit facilities for lenders and borrowers. Moreover, this significantly decreases the risk of fraudulent activities and the customer's financial loss. The cyber security risk and the privacy concerns of the user can be addressed through the use of AI in order to maintain financial stability at banks. It is used in social media analytics to scan banking-related data and develop a model for predicting future product demands. The AI-based system can detect financial fraud in banks, thus making the system more secure and safe (Li et al., 2021; Pourhabibi et al., 2020). Figure 1 describes the process adopted by AI for providing customer service in banks with different layers of sourcing, application, building, and delivery. Customer query response time is a crucial factor in banks' performance and support in customer acquisition. Chatbot, an AI-enabled technology, is extensively used in banks for customer service and relationship management are tested with cognitive capabilities to improve the service and interaction process in India. However, other areas, such as operation, authentication, and payment system, require automation in India. So, the demand for AI in banks will increase in India. The process of determination of credit worthiness of banking customers can be done through the predictive models of AI. Rapid improvements in the digital divide can be initiated with the emergence of AI technology in the banking and financial sector. AI system is employed on non-traditional data such as patterns of social media usage, internet browsing history, and Global Positioning System (GPS) records for locations to analyse the demand of the banking customer (Meghani, 2020).

Figure 1: Process of AI-Enabled Technology in Customer Service at Banks



Notes: CRM: Customer relationship management

AI's acceleration rate in recent years has proved that automation is the future of banking. Banks' futuristic scope lies in employing the Banking-as-a-Service (BaaS) platform for developing an ecosystem focusing on a data-centric approach. It can reap significant benefits for the long-term goal of the business and assist in growth. A robust digital base can be developed through AI-enabled technologies for database management, such as storage, cleaning, and categorizing the profile of the customers accordingly (Pu et al., 2021). So, AI implementation in the future requires understanding the vital factors, and the banking authorities must know which areas need more attention than others. Moreover, the service industry's competitive environment allows customers to switch from one bank to another easily. This study will highlight the retention part from the implementation and customer retention sense. The former banking channels concentrated on cross-channel interaction with the customers; however, customer demands have significantly changed the intuitive, customized, and omnichannel experience (Chakravaram et al., 2021). The personalized engagements of customers for attaining financial objectives are the key to customer satisfaction and loyalty which can be easily performed by AI (Kant and Jaiswal, 2017). The extant literature also focused on the advantages of AI and the dependencies related to it. These are significant in studying the acceptability and hence implementing it in future.

It is evident from the above discussion that customers' experience will be amplified to a more significant extent with the inclusion of AI in customer interaction and banking services. The present study seeks to contribute to the banking domain by evaluating the importance of AI in customer service interaction and identifying fraudulent activities. Although Indian banks are yet to adopt AI, extant literature based on this study found numerous uses of AI-enabled technology in banking operations worldwide (Milana and Ashta, 2021; Ahmed, 2021). The problems arising out of AI execution in banks necessitate the need to study the factors that influence the adaptation behaviour of the customer (Ryzhkova et al., 2020). Therefore, in this paper, to measure the extent of acceptability of AI in Indian banking services, the driving factors for adopting AI-based technology are studied in detail and subsequently ranked according to their importance from the customers' perspective. This will bring innovation in customer service in the banking industry and guide the policymakers to frame appropriate fundamentals related to AI. The factors are prioritized based on their importance and their interdependence on each other. The relatedness of the drivers serves the purpose of a specific application of AI in banks, which can be resolved through a multi-criteria decision-making (MCDM) tool (R et al., 2021; Černevičienė et al., 2022). The nature of the problem reveals that the data and information provided are unpredictable. Hence, the decision-making trial and evaluation laboratory (DEMATEL) technique is applied for ranking the factors using peer comparison and derivation of a causal diagram for understanding. It visualizes the qualitative judgments of the expert's opinions and existing literature into a clearly defined rational structure. The study's findings pave the way for policymakers and bankers to introduce AI in their systems, keeping in mind the significance of factors as per the result obtained in this study. Overall, the end user, i.e., customers, will be able to adapt to the technology efficiently and benefit in the long run. For this process, several factors were considered that promote AI usage in banks, and those factors were segregated into cause and effect using the DEMATEL method.

The rest of the paper is as follows: Section 2 provides a brief literature review, Section 3 discusses the research gap and objectives, Section 4 describes the research methodology, Section 5 discusses the findings, Section 6 concludes the study, and Section 7 discusses a few practical implications, limitations, and scope for future research.

2. Review of Literature

The previous literature provides ample scope and possibilities of AI in banks and how it can reshape the banking environment in the future. The emergence of Fintech companies which are handling large volumes of data and utilizing those data to study customer behaviour and expenditure pattern, creates their own identity in the financial industry apart from banks (Milian et al., 2019; Gomber et al., 2018). According to Sharma and Sharma (2019), the most financial transaction takes place via mobile phone, which changes the traditional mode of communication to an advanced application in banking. However, more than mobile banking is needed to utilise more resources or ideas to capture, store, segregate, and utilize data for determining customers' perceptions (Shareef et al., 2018; Chawla and Joshi, 2017). The introduction of newer technologies in the banking industry is a two-way process, where the customer acceptability of the technology is of utmost importance (Alalwan et al., 2018; Asadi et al., 2017). The various technologies introduced in Turkish, Chinese, and Persian banks have been mentioned in Table I for reference. None have applied the F-DEMATEL technique to AI implementation in the Indian banking industry. Although many drivers were undertaken for the research conducted by (Humbani and Wiese, 2018), convenience and compatibility with online payment services were of utmost importance (Lin et al., 2020; Shaikh et al., 2020). The marketing of AI dramatically depends on the quality of users, the development of the country, and the scope of operation by industry (Kopalle et al., 2021; Chen et al., 2021; Wang et al., 2021). AI-based technology facilitates automation in the service industry, and the customer feels they are in charge of the decisions more than the physical approach (Subero-Navarro et al., 2022; Khatib, 2021; Königstorfer and Thalmann, 2020). The significant advantage of AI in banks is personalized customer interaction, cost reduction, and opportunities for establishing recent business models to compete in the market (Joshi and Ranjan, 2021; Kaur et al., 2020; R et al., 2021). Additionally, AI will have a significant role in extracting data and applying analytics to provide the required results (Luna et al., 2019; He et al., 2021). Virtual assistant such as chatbots in bank facilitates customer relationship management, reduction of workload, and saves time (Kumar et al., 2018; El-Gohary et al., 2021; Muthukannan et al., 2020). Ibrahim and Nwobilor (2020) and Tang and Tien (2020) highlighted the ease of complicated data handling of customers through AI-enabled technologies in banks. It also provides opportunities for decision-making during banking operations and customer service in Indian banks (Sepehri-Rad et al., 2019; Maheswaran and Benaka Santhosh, 2021; Anagnostopoulos, 2018). The present study employs the DEMATEL technique to identify factors necessary for establishing AI-enabled technology in banking. The suitability of the research methodology is governed by studying different studies conducted using similar techniques in several countries' banking and financial arena (Gupta et al., 2022; Rahman et al., 2021). Table I gives a detailed description of the information study according to similar research methodology applied in different banking industries. The extant study unearths factors necessary for implementing AI related to customer service in a finite way. Hence, the present study focuses on the crucial factors for AI implementation in the banking environment from the perspective of customer acceptability.

Table 1: Tabular Elaboration of Similar Research Methodology Applied in Different Sectors

S no.	Area of application of AI	Description	Methodology	Author(s)
1.	E-commerce	Evaluation of the authentication process in online banking at Parsian Bank	DEMATEL	Sepehri-Rad *et al.*, 2019
2.	Indian banking industry	Success factors for evaluation of E-service quality	Analytical Hierarchical process (AHP)– Technique for order performance by similarity to ideal solution) TOPSIS–DEMATEL approach	Agrawal *et al.*, 2020
3.	Safety and Risk analysis	Risk factors and sources of information	DEMATEL with Best Worst method and Bayesian network (BN)	Yazdi *et al.*, 2020
4.	E-commerce	Identification and prioritization of factors	Interpretive structural modelling (ISM) and fuzzy analytical process	Valmohammadi and Dashti, 2016
5.	European Banking Sector	Analysis of Incremental and Disruptive Innovation Policies	DEMATEL, TOPSIS, VIKOR	Dincer *et al.*, 2019
6.	Banking industry	Determine criteria for selection of location for new bank branches	Fuzzy-DEMATEL	Vafadarnikjoo *et al.*, 2015
7.	Behavioural psychology	Addiction to social media	DEMATEL	Dalvi-Esfahani *et al.*, 2019
8.	European banking sector	Evaluation of concentration and competition of different places in Europe	Fuzzy DEMATEL, fuzzy ANP, and fuzzy VIKOR	Dincer *et al.*, 2020
9.	Turkish banking sector	Comparison of financial performance of Turkish banks	DEMATEL, Grey Relational Analysis (GRA) and MOORA approach	Yüksel *et al.*, 2017
10.	Banking industry	Factors responsible for adoption of internet banking	DEMATEL-ANP-SEM approach	Lin *et al.*, 2020

S no.	Area of application of AI	Description	Methodology	Author(s)
11.	European banking industry	Evaluation of investment in Fintech	Fuzzy DEMATEL, Fuzzy TOPSIS, and Fuzzy VIKOR	Kou *et al.*, 2021
12.	Business analytics	Human resource selection in an organization	DEMATEL and Elimination and Choice Expressing the Reality (ELECTRE)	Kilic *et al.*, 2020
13.	Banking industry	Factors responsible for information technology outsourcing in banks	Fuzzy-DEMATEL	Gerami and Feili, 2016
14.	Chinese banking industry	Factors for improvement of financial innovation in banks	F-DEMATEL, Analytic network process (ANP), and VIKOR approach	Zhao *et al.*, 2019
15.	Manufacturing industry	Investor perception for selection of industry	Fuzzy hybrid Analytical model	Dincer *et al.*, 2016

Notes: This table provides a summary of extant literature to which this study contributes.

3. Research Gap and Objectives

The current research study revealed the utilization of AI-based technology in different fields for customer service interaction and handling of operational procedures in the organization. The extant literature focused on the utilization of AI, the implications of AI in a marketing sense, and its primary benefit in the service industry. Although AI is replacing tasks that are mundane and repetitive. However, the research study conducted formerly provides data that is uncertain in nature and inconsistent in banks. Few researchers have focused on the customer acceptability of AI-based technologies in banks in developing countries such as India. To bridge this gap, the present study employs the Fuzzy-DEMATEL approach to remove vagueness and thoroughly evaluate the factors influencing the use of AI-based technology in the banking industry. The extant literature addresses the factors necessary for establishing AI-enabled technologies in banking from the perspective of customer acceptability in a limited manner. The concept of addressing the drivers related to customer acceptability that influence the practice of AI in banking that incorporates the Fuzzy-DEMATEL technique is novel. This assessment of the factors will play a crucial role in determining its futuristic implication for banking customers and pave the way for successful implementation by policymakers.

This study sets out to find the relative association among the factors and resolution of entangled issues related to AI-enabled technology in banks through an impact relation graph. The primary objectives of this research study are as follows:

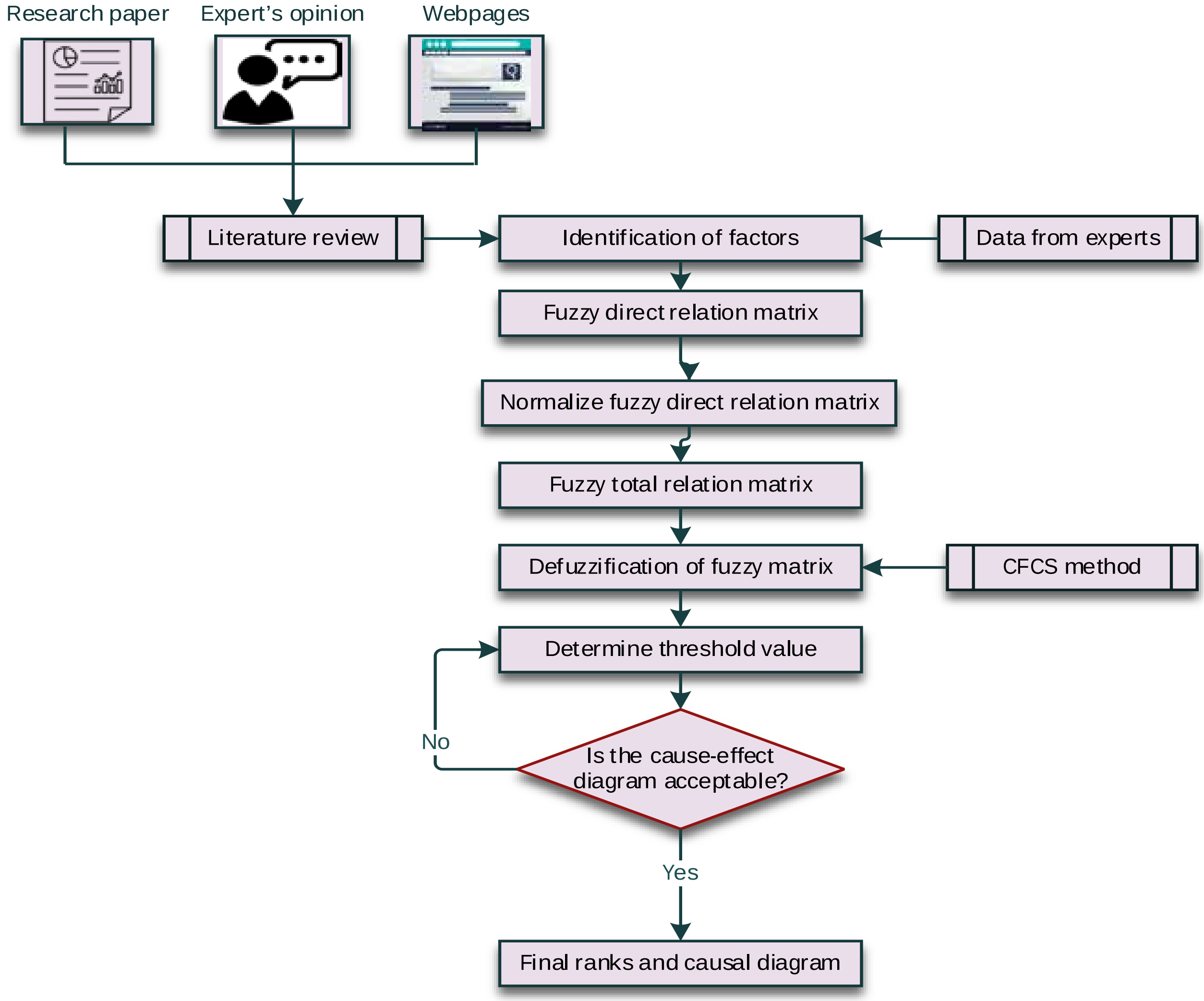
a) Identification of factors for AI-enabled technology adoption by banking customers
b) Rank the factors crucial for AI-enabled technology adoption according to their importance
c) Analyse cause and effect relationship among the factor that determine AI-enabled technology adoption

4. Research Methodology

To address the objectives mentioned above, the factors were determined using the existing studies and supplicate input from the experts in the Indian banking industry. The cause-and-effect relationship was determined using a decision-making trial and evaluation laboratory (DEMATEL). The factors considered are independent of each other from the theoretical perspective. However, each factor is interdependent on the other in real life. This inter-relatedness is evaluated well by the

DEMATEL technique and specifies the extent of the influence of one factor on the other. Evaluating the correlation of the drivers of AI-enabled technology in banks through DEMATEL is most appropriate for prioritizing the factors according to their importance. Moreover, this technique clearly distinguishes the cause-and-effect drivers from the factors for problem measurement. This technique is widely used in various industries worldwide, such as manufacturing (Shavarani et al., 2018; Dincer et al., 2016), medical (Longoni et al., 2019), supply chain (Chang et al., 2011), and e-commerce (Chiu et al., 2014; Sepehri-Rad et al., 2019) to address and prioritize the influence of the factors based on peer comparison method. The results further assist the clear directions and importance of the selected factors during evaluation. Figure 2 illustrates the DEMATEL technique.

Figure 2: Framework for the Current Study



Notes: The figure depicts the research flow of the study, starting from the source of data collected and analysis of the results obtained.

4.1 Survey Instrument

In a practical sense, the expert opinion in the case of DEMATEL tends to be qualitative with the use of linguistic terms. Hence, the technique utilizes fuzzy set theory to convert these qualitative values into a crisp form. The questionnaire was disseminated to the intended experts through e-mail, and the response was collected through the same medium. The Likert scale was used for filling up the responses starting from 0-4, where 0 means "Very low impact" and 4 means "Very high impact." Altogether, ten experts were selected, i.e., five from the banking domain and five from the academic domain, to express their views on this subject. All the experts possess more than five years of work experience in their respective domains. The experts from the banking domain include the Product manager, the Head of the banking and operation department in the retail banks, the Head of customer service and operations, the Business head, and the Cluster head. There were Associate professors, Professors, and Dean (research and consultancy) from the academic domain.

The Cronbach Alpha of the self-designed questionnaire was 0.86, indicating the high reliability of the questions asked. The value of Cronbach alpha lies between 0 to 1, where 0 signifies no reliability and 1 indicates the highest reliability. Usually, a reliability of more than 0.7 is considered apt for a research study (Prentice and Nguyen, 2021; Sepehri-Rad et al., 2019).

4.2. Flow of Methodology Adopted

Step 1: Identification of factors responsible for customer adoption of AI-based technology in the banking sector.

The factors were determined through a literature survey obtained from published research articles and conference proceedings extracted from different databases, including Scopus and Web of Science. The basis of the selection of the research paper was recency and relevancy with the topic. The experts were solicited for validation of those identified factors, and the purposive sampling technique was applied to select experts in the domain. Two sub-factors were eliminated after consultation with the experts as they were not significantly related to AI-based technology, and lastly, 15 sub-factors were considered important for the study. The factors were categorized into cognitive and mental behaviour, cultural and educational, risk and performance, and external aspects according to the significance of the AI-based technology. Table 2 elaborates the description of each factor in the context of AI-enabled banking technology.

Step 2: Construction of fuzzy direct relation matrix.

An 'n × n' matrix is created to compute the relationship among the factors given. A fuzzy number represents the influence of the element present in each row on the elements present in each column. Every expert input for further calculation must complete the fuzzy matrix. Lastly, the arithmetic mean of every expert's opinion is used to construct the direct relationship matrix termed as stated in Equation 1.

$$a = \begin{bmatrix} 0 & \cdots & \tilde{\tilde{a}}_{n1} \\ \vdots & \ddots & \vdots \\ \tilde{a}_{1n} & \cdots & 0 \end{bmatrix} \tag{1}$$

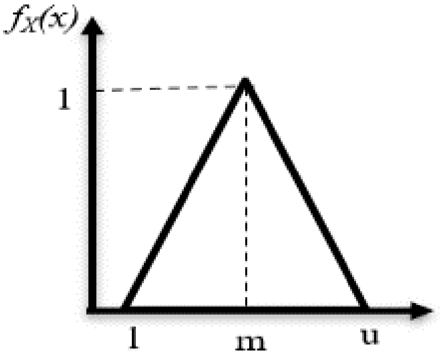
For each element present column-wise, the matrix columns are divided into three parts representing *l*, *m*, and *u*. Since triangular fuzzy scales are used, the values of each input from 0-4 can be referred to from Table 3. Every member of the fuzzy set contains a degree of membership and a membership function. The membership function has a real number starting from zero to one. The triangular membership function is the most commonly used, having three values: *l*, *m*, and *u*. The triplet (*l*,*m*,*u*) where l$\leq m \leq u$ indicates the smallest, medium, and largest probable values, respectively. Figure 3 highlights the triangular membership function used in the fuzzy set.

Table 2: **Brief Description of the Drivers that impact Artificial Intelligence in Indian banks**

Factors	Sub-factors	Notation	Description	Source
Cognitive and mental behaviour	Perceived trust	D1	The degree to which customers perceive that AI technology is better than human interaction	Shareef *et al.,* 2018; Sharma and Sharma, 2019
	Social influence on customer	D2	The effect of social interaction and the flow of information among various generations of people determines the popularity of technology	Sivathanu *et al,* 2019; Alalwan *et al.,* 2018
	Attitude of customers toward AI	D3	Perceived cognitive and effective behavioral aspect; intention to use the service	Luna *et al.,* 2019; Mehrad and Mohammadi, 2017
Cultural and education	Awareness level of AI	D4	The extent to which customer believes that AI learn enough information, including consciousness	Hassija and Srivastava, 2020; Sabharwal, 2018
	Information quality	D5	Nature and variety of information provided	Qadiri *et al.*, 2020; Shareef *et al.,* 2018
	Ease of use	D6	Utility and functional benefit to the customer; effortless, simple to learn, and use	Luna *et al.,* 2019; Humbani and Wiese, 2018; Johnson *et al.,* 2018
Risk and performance	Security of AI system	D7	The extent to which customer is ready to reveal personal and financial information during AI-enabled interaction devoid of misuse.	Sepehri-Rad *et al.,* 2019; Shareef *et al.,* 2018; R. and Ravi, 2021
	Efficiency of AI system	D8	Optimization of time and resources to produce quality service to a customer	Baabdullah *et al.,* 2019; Shareef *et al.,* 2018
	Transparency of information provided by AI	D9	Perceived openness of information from both ways	Joshi *et al.*, 2021; Prentice and Nguyen, 2021
	Satisfaction of customer	D10	The extent of fulfilment of customers' expectations and providing contentment	Karjaluoto, *et al.,* 2019; Arcand *et al.,* 2017; Asadi *et al.,* 2017
	Responsiveness	D11	Faster communication	Vafadarnikjoo *et al.,* 2015; Ravikumar *et al.,* 2021
External aspects	Government regulation of AI in banks	D12	The degree to which the laws and regulation has a controlling effect on the AI	Raj and Sah, 2019; Ramamurty *et al.*, 2021
	Perceived environmental consideration	D13	The impact of AI technology on the environment and global development	Truby *et al.*, 2020; Raj and Sah, 2019; Mhlanga, 2020
	Technical requirement	D14	Includes innovativeness and flexibility for the customer	Sepehri-Rad *et al.,* 2019; Raj and Sah, 2019; Karjaluoto, *et al.,* 2018
	Cost of AI technology	D15	Evaluation of price comparison with human interaction	Alalwan *et al.,* 2018; Ryu, 2018; Alzaidi, 2018

Note: The drivers are derived from existing literature studies and are used for prioritization of the factors accordingly.

Figure 3: **Triangular Membership Function**



Note: The triangular membership function has three values: l, m, and u. The triplet (l,m,u) where l≤ m ≤ u indicates the smallest, medium, and largest probable values.

Table 3 gives the linguistic scales used for the triangular fuzzy membership function. We provide the direct relation matrix (X_{n*n}) through the pairwise comparison of the values presented in the matrix given by the experts in Appendix A1.

Table 3: Fuzzy Scales

Fuzzy Code	Linguistic scales	L	M	U
0	No influence	0	0	0.25
1	Very low influence	0	0.25	0.5
2	Low influence	0.25	0.5	0.75
3	High influence	0.5	0.75	1
4	Very high influence	0.75	1	1

Note: The experts were given these linguistic scales for responses in a tabular fashion. The values in the responses have the linguistic scale accordingly.

Step 3: Normalize the fuzzy direct relation matrix.

The normalized fuzzy direct-relation matrix is computed by using the following formula given in Equation 2:

$$\tilde{x}_{ij} = \frac{\tilde{a}_{ij}}{k} = \left(\frac{l_{ij}}{k}, \frac{m_{ij}}{k}, \frac{u_{ij}}{k}\right) \tag{2}$$

where, the value of k is determined by Equation 3, and *i* and *j* vary from 1 to n.

$$k = \max_{i,j}\left\{\max_{i} \sum_{j=1}^{n} u_{ij}, \max_{j} \sum_{i=1}^{n} u_{ij}\right\} \qquad i,j \in \{1,2,3,\dots,n\} \tag{3}$$

Step 4: Calculation of fuzzy total-relation matrix.

The fuzzy total-relation matrix is obtained through the following formula in step 4, and the value of Z is generated by equation 4:

$$\tilde{Z} = \lim_{r \to +\infty} (\tilde{x}^1 \oplus \tilde{x}^2 \oplus \ldots \oplus \tilde{x}^k) \tag{4}$$

Assuming that if every element of the fuzzy total-relation matrix is represented as $\tilde{p}_{ij} = (l''_{ij}, m''_{ij}, u''_{ij}$, it is calculated as follows in the subsequent Equations 5, 6, and 7.

$$[l''_{ij}] = x_l \times (I - x_l)^{-1} \tag{5}$$

$$[m''_{ij}] = x_m \times (I - x_m)^{-1} \tag{6}$$

$$[u''_{ij}] = x_u \times (I - x_u)^{-1} \tag{7}$$

To illustrate, the inverse of the normalized matrix is computed firstly, and secondly, it is subtracted from matrix I, and lastly, the normalized matrix is multiplied by the resulting matrix.

Step 5: Defuzzification of the fuzzy matrix into crisp values

Cheng and Hwang introduced Converting Fuzzy data into Crisp Scores (CFCS) method in 1992 to uncomplicate some of the steps in DEMATEL. The resulting fuzzy scores are converted to crisp values using a technique similar to that used to calculate the left and right scores using fuzzy minimum and fuzzy maximum, respectively, and the total score is calculated using the membership functions as a weighted average. The alternatives are calculated according to the i^{th} criteria with fuzzy numbers. The steps of the CFCS method are as follows:

$$l_{ij}^{n} = \frac{\left(l_{ij}^{p} - \min l_{ij}^{p}\right)}{\Delta_{min}^{max}} \tag{8}$$

$$m_{ij}^{n} = \frac{(m_{ij}^{p} - min\ l_{ij}^{p})}{\Delta_{min}^{max}} \tag{9}$$

$$u_{ij}^{n} = \frac{(u_{ij}^{p} - min\ l_{ij}^{p})}{\Delta_{min}^{max}} \tag{10}$$

So that,

$$\Delta_{min}^{max} = \max u_{ij}^{p} - \min l_{ij}^{p} \tag{11}$$

Computation of the upper and lower bounds of normalized values known as fuzzy min and fuzzy max

$$l_{ij}^{t} = m_{ij}^{n} \Big/ (1 + m_{ij}^{n} - l_{ij}^{n}) \tag{12}$$

$$u_{ij}^{t} = u_{ij}^{n} \Big/ (1 + u_{ij}^{n} - l_{ij}^{n}) \tag{13}$$

Determining the total normalized crisp values, which is a weighted average according to the membership functions

$$x_{ij} = \frac{[l_{ij}^{t}(1 - l_{ij}^{t}) + u_{ij}^{t} \times u_{ij}^{t}]}{[1 - l_{ij}^{t} + u_{ij}^{t}]} \tag{14}$$

The result of the CFCS algorithm is crisp values as given in Table 4, and the calculations are expressed from Equations 8-14 mentioned above.

Table 4: Crisp Values of the Fuzzy Numbers Obtained

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14	D15
D1	0.1890	0.2117	0.2384	0.2054	0.2162	0.2230	0.2029	0.2091	0.2198	0.2398	0.2407	0.2152	0.2204	0.2237	0.1922
D2	0.2346	0.1783	0.2371	0.2434	0.2299	0.2219	0.2396	0.2235	0.2201	0.2106	0.2109	0.2292	0.2030	0.2211	0.1905
D3	0.2327	0.2098	0.1888	0.2419	0.2122	0.2043	0.2364	0.2219	0.2015	0.2234	0.2088	0.2402	0.2187	0.2351	0.1899
D4	0.1953	0.2214	0.2476	0.2093	0.2540	0.2323	0.1907	0.2179	0.2286	0.2352	0.2216	0.2507	0.2122	0.2480	0.2457
D5	0.2214	0.1966	0.2056	0.2143	0.1699	0.1772	0.2377	0.1928	0.2049	0.2125	0.2259	0.1821	0.1727	0.2067	0.2070
D6	0.1922	0.1860	0.2268	0.2188	0.2062	0.1643	0.2285	0.2139	0.2087	0.1994	0.2159	0.2189	0.1769	0.2280	0.2270
D7	0.2264	0.2180	0.1970	0.2040	0.2341	0.1972	0.1826	0.1989	0.1955	0.2168	0.2028	0.2191	0.2103	0.2118	0.1828
D8	0.2088	0.2352	0.2462	0.2534	0.2391	0.2146	0.2325	0.1845	0.2266	0.2464	0.2348	0.2372	0.2267	0.2311	0.2310
D9	0.2274	0.2095	0.2151	0.2067	0.2082	0.2165	0.2316	0.2012	0.1646	0.2189	0.2042	0.2062	0.1963	0.2099	0.1843
D10	0.2498	0.2255	0.2527	0.2598	0.2449	0.2054	0.2384	0.2495	0.2316	0.1929	0.2536	0.2276	0.2440	0.2525	0.2376
D11	0.2318	0.2085	0.2349	0.2415	0.2287	0.2039	0.2063	0.2046	0.1842	0.2065	0.2156	0.2256	0.1999	0.2474	0.2209
D12	0.2092	0.2189	0.2076	0.2191	0.1891	0.1968	0.2280	0.2136	0.1924	0.1835	0.1992	0.1717	0.2225	0.2271	0.2127
D13	0.2376	0.2297	0.2272	0.2035	0.1884	0.2210	0.2121	0.1970	0.1763	0.2184	0.1991	0.2185	0.1600	0.2258	0.2111
D14	0.1835	0.2077	0.2311	0.2247	0.2127	0.2044	0.1885	0.1890	0.2148	0.1748	0.2211	0.1788	0.1818	0.1698	0.2181
D15	0.2264	0.2179	0.2036	0.2135	0.2375	0.2152	0.2319	0.2297	0.1809	0.2023	0.2237	0.2048	0.1778	0.2285	0.1675

Note: The crisp values have been obtained after using a technique similar to that used to calculate the left and right scores using fuzzy minimum and fuzzy maximum, respectively, and the total score is calculated using the membership functions as a weighted average.

Step 6: Determine the threshold value.

The threshold value is determined to calculate the total internal relations matrix. It is adequate to compute the average values of matrix T to determine the threshold value for relations. After determining the threshold intensity, the values present in the matrix T, which are lesser than the threshold value, are set to zero. Accordingly, the threshold value is equal to 0.075471698 in this study. Hence, all the values in matrix T, which are smaller than 0.075471698, are set to zero; that is, the causal relation is not considered. The values greater than 0.075471698 are set to one. The result obtained after computing the threshold value is mentioned in Table 5.

Table 5: The Crisp Total- Relationships Matrix by Considering the Threshold Value

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14	D15
D1	0	0	1	0	1	1	0	0	1	1	1	1	1	1	0
D2	1	0	1	1	1	1	1	1	1	0	0	1	0	1	0
D3	1	0	0	1	0	0	1	1	0	1	0	1	1	1	0
D4	0	1	1	0	1	1	0	1	1	1	1	1	0	1	1
D5	1	0	0	1	0	0	1	0	0	0	1	0	0	0	0
D6	0	0	1	1	0	0	1	0	0	0	1	1	0	1	1
D7	1	1	0	0	1	0	0	0	0	1	0	1	0	0	0
D8	0	1	1	1	1	1	1	0	1	1	1	1	1	1	1
D9	1	0	1	0	0	1	1	0	0	1	0	0	0	0	0
D10	1	1	1	1	1	0	1	1	1	0	1	1	1	1	1
D11	1	0	1	1	1	0	0	0	0	0	1	1	0	1	1
D12	0	1	0	1	0	0	1	0	0	0	0	0	1	1	0
D13	1	1	1	0	0	1	0	0	0	1	0	1	0	1	0
D14	0	0	1	1	0	0	0	0	1	0	1	0	0	0	1
D15	1	1	0	0	1	1	1	1	0	0	1	0	0	1	0

Note: The threshold value is equal to 0.075471698 in this study. All values in matrix T, which are smaller than 0.075471698, are set to zero; that is, the causal relation is not considered. The values greater than 0.075471698 are set to one.

Step 7: Determine the final output and construct a causal relation diagram.

The final output is obtained by calculating the sum of each row and each column of T (in step 4). The sum of rows is expressed as C, and the sum of columns is expressed as R, which are calculated as per Equations 15 and 16:

$$C = \sum_{j=1}^{n} T_{ij} \tag{15}$$

$$R = \sum_{i=1}^{n} T_{ij} \tag{16}$$

Table 6: Final Output of the Fuzzy Matrix

	C	R	C+R	C-R	Horizontal vector rank of C+R	Vertical vector rank of C-R
D1	3.2476	3.266	6.5136	-0.0183	6	10
D2	3.2935	3.1746	6.4681	0.1189*	7	3
D3	3.2656	3.3596	6.6252	-0.0941	3	11
D4	3.4104	3.3592	6.7697	0.0512*	1	5
D5	3.0274	3.2712	6.2986	-0.2438	11	14
D6	3.1115	3.0979	6.2094	0.0136*	13	8
D7	3.0973	3.2878	6.385	-0.1905	8	13
D8	3.4482	3.1471	6.5953	0.3010*	4	2
D9	3.1005	3.0507	6.1513	0.0498*	14	6
D10	3.5656	3.1813	6.7469	0.3843*	2	1
D11	3.2602	3.2779	6.5382	-0.0177	5	9
D12	3.0914	3.2256	6.3171	-0.1342	10	12
D13	3.1258	3.0233	6.1491	0.1025*	15	4
D14	3.0007	3.3665	6.3672	-0.3657	9	15
D15	3.1612	3.1183	6.2795	0.0430*	12	7

*Notes: * indicate the causal factors. C+R represents the degree of importance of factor i in the entire system, and C-R represents the net influence of factor i that contributes to the system.*

Then, the values of C+R and C-R are calculated using the given values of C, and R. C+ R is called prominence, whereas C-R is called relation. C+R represents the degree of importance of factor *i* in the entire system, and C-R represents the net influence of factor *i* that contributes to the system. Table 6 shows the final output.

Figure 4 presents the model of significant relations of the factors where the values of (C+R) is arranged on the horizontal axis, and the values of (C-R) is arranged on the vertical axis. Figure 5 states the graphical visualization of the overall research process.

Figure 4: Causal Diagram of the Result Obtained

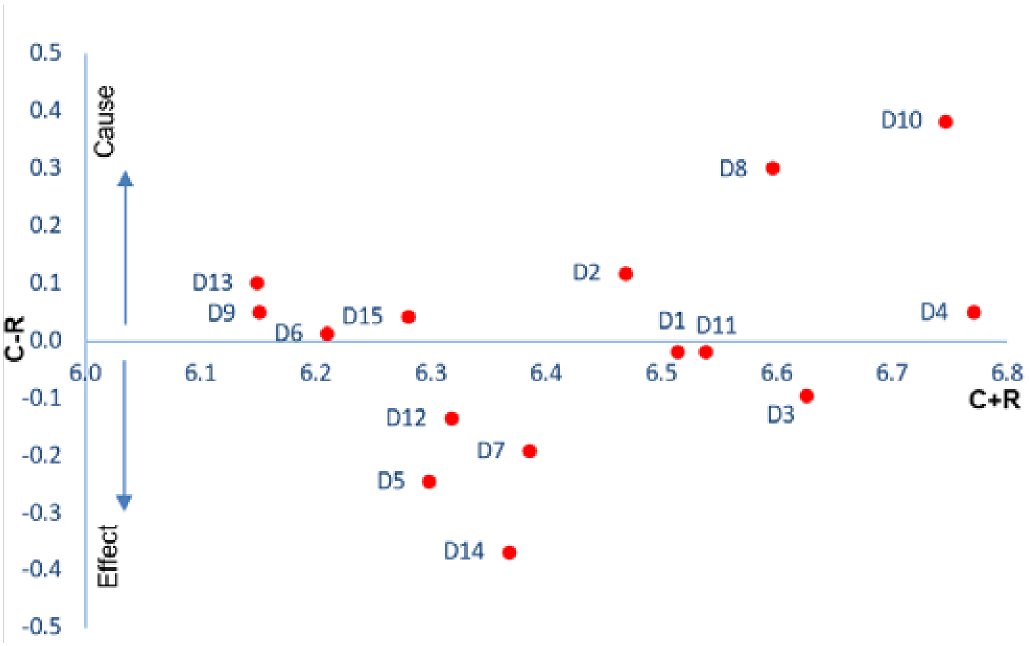
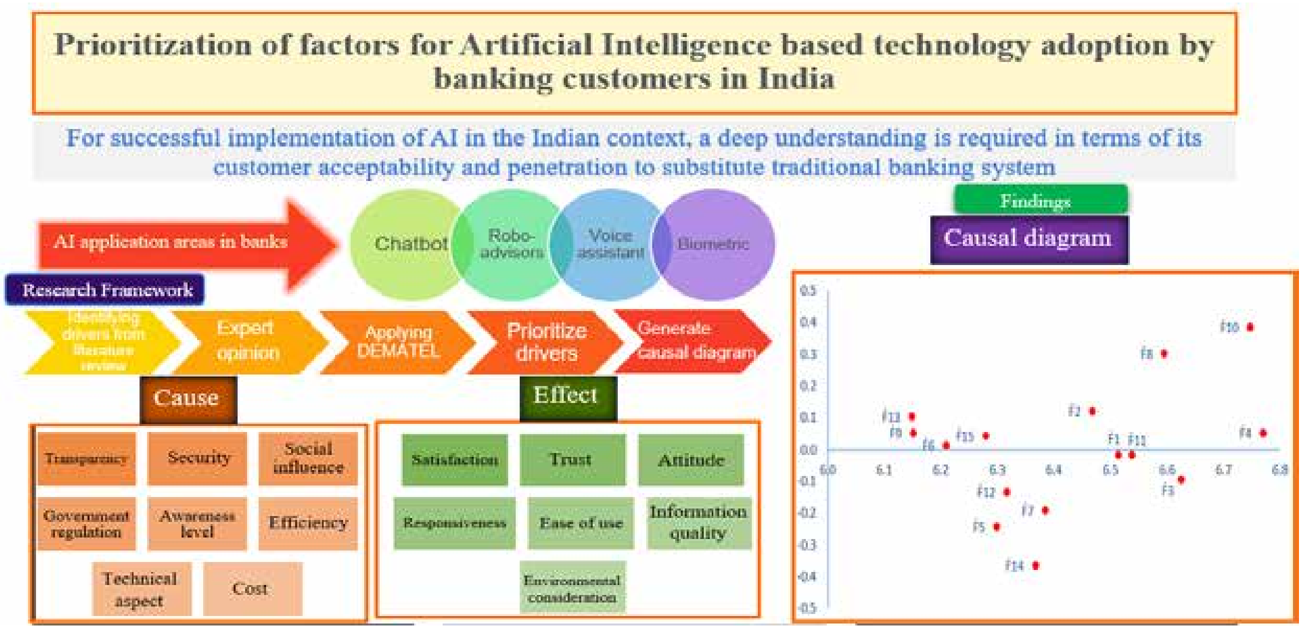


Figure 5: Graphical Visualization of the Research Process



5. Findings and Discussion

The categorization of the sub-factors leads to a greater understanding of the influence in a proportionate direction with the help of a digraph. The factors are divided into cause-and-effect groups based on the result. The cause group comes from (C-R>0), and the effect group comes from (C-R<0), and a causal diagram is mapped. The causing factor influences the entire system, and their execution affects the study's overall objective. Table 7 clearly shows the factors divided into cause and effect according to the result obtained. The results are in line with the former literature conducted in this field.

Table 7: Differentiation of Factors into Cause and Effect of AI-based Technology in the Banking Sector

S No.	Causal factors	S No.	Effectual factors
1	Transparency of information provided by AI (D9)	1	Satisfaction of customer (D10)
2	Security of AI system (D7)	2	Perceived trust (D1)
3	Social influence on customer (D2)	3	Attitude of customer towards AI (D3)
4	Government regulation of AI in banks (D12)	4	Responsiveness (D11)
5	Awareness level of AI (D4)	5	Ease of use (D6)
6	Efficiency of AI system (D8)	6	Information quality (D5)
7	Technical requirement (D14)	7	Perceived environmental consideration (D13)
8	Cost of AI technology (D15)		

Note: The factors are classified into cause and effect according to the result obtained.

The study analysed the customer acceptability towards AI-enabled technologies in Indian banks through the application of MCDM methodology. Based on the results obtained through DEMATEL analysis, the factors are arranged according to the extent of the measured impact on AI. The final values of eight causal and seven effect factors are presented in Table 7. The cause factors are transparency of information provided by AI (0.0498), security of AI-enabled system (0.3010), social influence on customers (0.1189), government regulation of AI in banks (0.1025), the awareness level of AI (0.0512), the efficiency of AI system (0.0498), the technical requirement (0.0430), and cost of AI-enabled technology (0.0136). The effectual factors are the satisfaction of customers (-0.0177), perceived trust (-0.0183), the attitude of customers towards AI (-0.0941), responsiveness (-0.1342), ease of use (-0.1905), information quality (-0.2438), and lastly perceived environmental consideration (-0.3657). In other words, it can be framed as D9>D7>D2>D12>D4>D8>D14>D15>D10>D1>D3>D11> D6>D5>D13. The ranking of different factors is discussed in detail.

5.1. Discussion on Major Causal Factors

This analysis reveals that the banking authorities and decision-makers in the financial industry should focus more on the transparency of information provided by AI-enabled technologies. Therefore, the sub-factor 'transparency of information provided by AI-enabled system (D9)' under the factor risk and performance is the most crucial factor in determining its successful implementation in banks, according to the expert's opinion. Factor D9 has an influential impact on the other seven factors. Information transparency will be prevalent if the data fed into the AI system is complete and accurate (Joshi *et al.*, 2021; Prentice and Nguyen, 2021).

The second most important sub-criteria is 'security of AI-based technologies (D7)' under the factor risk and performance. Apparently, due to rising cases of fraudulent activities, security is an important aspect the banks must work upon. The breach of data and dissemination of unvalidated data can wrongly impact the relationship between the banks and their customers. The communication channel should be encrypted with security layers, and any trigger of failure should be communicated immediately (Sepehri-Rad *et al.,* 2019; Shareef *et al.,* 2018; R. and Ravi, 2021).

The third most vital sub-factor is 'social influence on the customer (D2)' under cognitive and mental behaviour. Nowadays, the bank's goodwill is also determined by the perception of its customers in respect of the latest technology used, and customers tend to distribute that information through social media and mass communication. This is why banks must be careful with their user's perceptions, and a continuous feedback system is encouraged for improvement (Sivathanu *et al.,* 2019; Alalwan *et al.,* 2018).

The fourth important sub-criteria is 'government regulation on AI in banks (D12)' under the criteria external factors. The governmental regulation on AI-based technology will determine the extent to which the customer can reap benefits from AI in banks in India (Raj and Sah, 2019; Ramamurty *et al.*, 2021).

The fifth important sub-factor is the 'awareness level of AI (D4)' under cultural and educational factors. In case of low awareness, the banking sector needs to train its customers about the AI-enabled platform and its advantages over the traditional banking system (Hassija and Srivastava, 2020; Sabharwal, 2018).

Similarly, the subsequent factors were organized as 'efficiency of AI-based system (D8)' under the driver risk and performance at sixth position, 'technical requirement (D14)' under the factor external aspect at the seventh vital sub-factor, 'cost of AI-based technology (D15)' under the factor external aspect as the eight most important sub-factor.

5.2. Discussion on major effectual factors

The ninth principle sub-factor is 'satisfaction of customer (D10)' under the risk and performance is most affected due to several given causes above. Hence, customer satisfaction must be of prime importance for banking officials while implementing AI-based technology for customer relationships and operational processes (Karjaluoto *et al.,* 2019; Arcand *et al.,* 2017; Asadi *et al.,* 2017).

The tenth key sub-driver is 'perceived trust (D1)' under the drivers of cognitive and mental behavior. The trust factor is vital for the growth of AI-enabled systems where the customers are ready to experiment with different forms of banking interaction and verification processes, such as biometrics and iris scanners, in the future (Shareef *et al.,* 2018; Sharma and Sharma, 2019).

The eleventh significant sub-criteria is the 'attitude of the customers towards AI (D3)' under cognitive and mental behavior criteria. The demand for AI will be shaped by the attitude formed by the customers toward AI and the faster response of AI compared to the manual mode of interaction (Luna *et al.,* 2019; Mehrad and Mohammadi, 2017).

Subsequently, the other effectual factors are stated as 'responsiveness (D11)' under the criteria risk and performance as the twelfth sub-criteria. The thirteen crucial sub-driver is 'ease of use (D6)' under the cultural and educational drivers. The fourteenth vital sub-factor is 'information quality of AI (D5)' under cultural and educational factors. Lastly, under the external driver aspect, the fifteen significant sub-driver is 'perceived environmental consideration (D13)'. The prioritization of the drivers necessary for successfully implementing AI-based technologies in banks will assist in providing alternatives for executing recent technology. The banks will be able to reposition their focus to establish AI as a medium for customer communication and perform smooth operational procedures, as discussed in past studies. The effectual factors can be controlled to provide favorable results to meet the banking sector's organizational goals in the future.

6. Conclusions

AI-based technologies have immense potential to change banks' traditional customer interaction and service scenarios through automated systems and technology. The best part about AI is that it positively contributes to environmental considerations for future and resource optimization. The stress on human resources may be reduced considerably due to the introduction of AI in fraud identification and detection of suspicious transactions of large volume by the customer through algorithmic architecture. The study's major objectives, such as identifying drivers, ranking of those drivers, and analysis of cause-and-effect drivers, are fulfilled through the literature review and expert opinion. The results of the DEMATEL technique state that driving factors significantly impact the practical application of the study undertaken. Additionally, this study's results emphasize the customer perception of the transparency of information provided by AI and the security features of AI in banks. Moreover, the causal factors directly influence customer satisfaction and trust in banks. Implementing AI is vital for the smooth flow of operations and requires planning with direction. The study guides those drivers crucial for the penetration of AI-based systems in Indian banks.

7. Practical Implications, limitations, and future research avenues

Since the concept of AI in banking is of recent origin in India, the results obtained in this study can be used as initial guidance to bear in mind the factors influencing AI incorporation in banks. The major objective of this paper is to provide a path for banking officials and regulators who are planning to encompass AI technology in their banking system in the future. Through adequate planning and clarification, the probability of success of implementation may be increased. The decision-makers working in this direction must focus on the perception of customers towards environmental consideration as well as the quality of the information provided by AI-based technology. Based on these factors and the acceptance rate in India, the financial regulatory agency (Reserve Bank of India) may focus on creating a digital penetration index. Due to the difficulty of quantifying the study's subjective factors, banks may create different scales of measurement compared to the customers' existing feedback systems. DEMATEL technique gives us clarity regarding the visualization of factors into fundamental (causal) and effect. Research practitioners who are applying the use of AI in banking may detect and identify their deprived areas through this study.

Future research studies may incorporate more than four factors and fifteen sub-factors for DEMATEL analysis. The output of the study is derived from the expert opinion related explicitly to AI-based banking systems, which cannot be generalized to other fields in banking. However, the results are fruitful for pursuing the scope of AI-enabled technologies in banking in the Indian scenario. It may be applied to different sectors or industries, such as manufacturing or telecommunication, dealing with the introduction of AI in their system to encourage an efficient result in the future. The technical complication can prove to be a major barrier to implementing successful AI-enabled technology in banks.

References

Agrawal, V., Seth, N. and Dixit, J.K. (2020), A combined AHP–TOPSIS–DEMATEL approach for evaluating success factors of e-service quality: an experience from Indian banking industry, *Electronic Commerce Research*, 1(1), 1–33.

Ahmed, R. (2021), Artificial Intelligence (AI) in Financial Sectors: blessings or threats?, 23(3), 20–25.

Alalwan, A.A., Dwivedi, Y.K., Rana, N.P. and Algharabat, R. (2018), Examining factors influencing Jordanian customers' intentions and adoption of internet banking: Extending UTAUT2 with risk, *Journal of Retailing and Consumer Services*, 40(1), 125–138.

Alzaidi, A.A. (2018), Impact of Artificial Intelligence on Performance of Banking Industry in Middle East, *IJCSNS International Journal of Computer Science and Network Security*, 18(10), 140.

Anagnostopoulos, I. (2018), Fintech and regtech: impact on regulators and banks, *Journal of Economics and Business*, 100(1), 1–35.

Arcand, M., PromTep, S., Brun, I. and Rajaobelina, L. (2017), Mobile banking service quality and customer relationships, *International Journal of Bank Marketing*, 35(7), 1066–1087.

Asadi, S., Nilashi, M., Husin, A.R.C. and Yadegaridehkordi, E. (2017), Customer's perspectives on adoption of cloud computing in banking sector, *Information Technology and Management*, 18(4), 305–330.

Baabdullah, A.M., Alalwan, A.A., Rana, N.P., Kizgin, H. and Patil, P. (2019), Consumer use of mobile banking (M-Banking) in Saudi Arabia: Towards an integrated model, *International Journal of Information Management*, 44(1), 38–52.

Buchanan, B.G. and Wright, D. (2021), The impact of machine learning on UK financial services, *Oxford Review of Economic Policy*, 37(3), 537–563.

Černevičienė, J., Kabašinskas, A. (2022), Review of Multi-Criteria Decision-Making Methods in Finance Using Explainable Artificial Intelligence. Frontiers in Artificial Intelligence., 5.

Chakravaram, V., Ratnakaram, S., Vihari, N.S. and Tatikonda, N. (2021), *The Role of Technologies on Banking and Insurance Sectors in the Digitalization and Globalization Era—A Select Study*, *Advances in Intelligent Systems and Computing*, 1245.

Chawla, D. and Joshi, H. (2017), Consumer perspectives about mobile banking adoption in India – a cluster analysis, *International Journal of Bank Marketing*, 35 (4), 616–636.

Chen, X., You, X. and Chang, V. (2021), FinTech and commercial banks' performance in China: a leap forward or survival of the fittest?, *Technological Forecasting and Social Change*, 166(1), 120–645.

Chiu, C. M., Wang, E. T., Fang, Y. H., & Huang, H. Y. (2014). Understanding customers' repeat purchase intentions in B2C E-commerce: The roles of utilitarian value, hedonic value and perceived risk. *Information Systems Journal*, 24, 85–114.

Dalvi-Esfahani, M., Niknafs, A., Kuss, D.J., Nilashi, M. and Afrough, S. (2019), Social media addiction: applying the DEMATEL approach, *Telematics and Informatics*, 43 (1), 101–250.

Dincer, H. (2019), HHI-based evaluation of the European banking sector using an integrated fuzzy approach, *Kybernetes*, 48(6), 1195–1215.

Dincer, H., Hacioglu, U., Tatoglu, E. and Delen, D. (2016), A fuzzy-hybrid analytic model to assess investors' perceptions for industry selection, *Decision Support Systems*, 86(1), 24–34.

Dinçer, H., Yüksel, S. and Martínez, L. (2020), A Comparative Analysis of Incremental and Disruptive Innovation Policies in the European Banking Sector with Hybrid Interval Type-2 Fuzzy Decision-Making Models, *International Journal of Fuzzy Systems*, 22(4), 1158–1176.

El-Gohary, H., Thayaseelan, A., Babatunde, S. and El-Gohary, S. (2021), An Exploratory Study on the Effect of Artificial Intelligence-enabled Technology on Customer Experiences in the Banking Sector, *Journal of Technological Advancements*, 1(1), 1–17.

Gerami, M. and Feili, H. (2016), Identification of Risk Factors in IT Outsourcing in Banks by using DEMATEL Fuzzy Method, *International Conference on Research in Science and Technology*, 1–14.

Gomber, P., Kauffman, R.J., Parker, C. and Weber, B.W. (2018), On the Fintech Revolution: Interpreting the Forces of Innovation, Disruption, and Transformation in Financial Services, *Journal of Management Information Systems*, 35(1), 220–265.

Gupta, S., Ghardallou, W., Pandey, D. K. and Sahu, G. P. (2022), Artificial intelligence adoption in the insurance industry: Evidence using the technology–organization–environment framework, *Research in International Business and Finance,* 63(1), 1-15.

Hassija, T. and Srivastava, P. (2020), Impact of Artificial Intelligence in customer satisfaction for Banking Industry, *International Journal of Advanced Science and Technology*, 29 (9s), 1947–1962.

He, X., Xiong, D., Khalifa, W.M.S. and Li, X. (2021), Chinese banking sector: A major stakeholder in bringing fourth industrial revolution in the country, *Technological Forecasting and Social Change*, 165(1), 120–519.

Humbani, M. and Wiese, M. (2018), A Cashless Society for All: Determining Consumers' Readiness to Adopt Mobile Payment Services, *Journal of African Business*, 19(3), 409–429.

Ibrahim, U.A. and Nwobilor, C.J. (2020), Artificial Intelligence as a Tool for Decision Making: A Perspective from the Central Bank of Nigeria, *International Journal of Managerial Studies and Research*, 8(1), 76–85.

Johnson, V.L., Kiser, A., Washington, R. and Torres, R. (2018), Limitations to the rapid adoption of M-payment services: Understanding the impact of privacy risk on M-Payment services, *Computers in Human Behavior*, 79 (1), 111–122.

Joshi, S., Tiwari, S. and Bharadwaj, S. (2021), A Study of Impact of Cloud Computing and Artificial Intelligence on Banking Services, Profitability and Operational Benefits, *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, 12(6), 1617–1627.

Joshi, V. and Ranjan, P. (2021), Importance and value of Artificial Intelligence in Financial Sector – a critical Review, *International Journal for Modern Trends in Science and Technology*, 7(5), 6–11.

Kant, R. and Jaiswal, D. (2017), The impact of perceived service quality dimensions on customer satisfaction: an empirical study on public sector banks in India, *International Journal of Bank Marketing*, 35(3), 411–430.

Karjaluoto, H., Shaikh, A.A., Saarijärvi, H. and Saraniemi, S. (2019), How perceived value drives the use of mobile financial services apps, *International Journal of Information Management*, 47(1), 252–261.

Kaur, N., Sahdev, S.L., Sharma, M. and Siqqiqui, L. (2020), Banking 4.0: the Influence of Artificial Intelligence on the Banking Industry & How AI is Changing the Face of Modern Day Banks, *International Journal of Management*, 11(6), 577–585.

Khatib, A.S. el. (2021), Machine Learning and Finance: A Review Using Latent Dirichlet Allocation Technique (LDA), *International Journal for Innovation Education and Research*, 9(4), 29–55.

Kilic, H.S., Demirci, A.E. and Delen, D. (2020), An integrated decision analysis methodology based on IF-DEMATEL and IF-ELECTRE for personnel selection, *Decision Support Systems*, 137(1), 113-121.

Königstorfer, F. and Thalmann, S. (2020), Applications of Artificial Intelligence in commercial banks – a research agenda for behavioral finance, *Journal of Behavioral and Experimental Finance*, 27(1), 1–35.

Kopalle, P.K., Gangwar, M., Kaplan, A., Ramachandran, D., Reinartz, W. and Rindfleisch, A. (2021), Examining artificial intelligence (AI) technologies in marketing via a global lens: current trends and future research opportunities, *International Journal of Research in Marketing*, 1(1), 1–19.

Kou, G., Olgu Akdeniz, Ö., Dinçer, H. and Yüksel, S. (2021), Fintech investments in European banks: a hybrid IT2 fuzzy multidimensional decision-making approach, *Financial Innovation*, Springer Berlin Heidelberg, 7(39), 1–28.

Kumar, K.S., Tamilselvan, S., Sha, B.I. and Harish, S. (2018), Artificial Intelligence Powered Banking Chatbot, *International Journal of Engineering Science and Computing*, 8(3), 16134–16137.

Li, Y., Yi, J., Chen, H. and Peng, D. (2021), Theory and application of artificial intelligence in financial industry, *Data Science in Finance and Economics*, 1(2), 96–116.

Lin, R.J. (2013), Using fuzzy DEMATEL to evaluate the green supply chain management practices, *Journal of Cleaner Production*, 40(1), 32–39.

Lin, W.R., Wang, Y.H. and Hung, Y.M. (2020), Analyzing the factors influencing adoption intention of internet banking: applying DEMATEL-ANP-SEM approach, *PLoS ONE*, 15(2), 1–25.

Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to medical artificial intelligence, *Journal of Consumer Research*, 46(4), 629–650.

Luna, I.R., Liébana-Cabanillas, F., Sánchez-Fernández, J. and Muñoz-Leiva, F. (2019), Mobile payment is not all the same: the adoption of mobile payment systems depending on the technology applied, *Technological Forecasting and Social Change*, 146(1), 931–944.

Maheswaran, M. and Benaka Santhosh, S. (2021), A Novel Approach for Analysis of Feedback in Banking System using Machine Learning Algorithm, *International Journal of Engineering Research & Technology*, 9(12), 11–13.

Meghani, K. (2020), Use of Artificial Intelligence and Blockchain in Banking sector: a study of Scheduled commercial banks in India, *Indian Journal of Applied Research*, 10(8), 10–13.

Mehrad, D. and Mohammadi, S. (2017), Word of Mouth impact on the adoption of mobile banking in Iran, *Telematics and Informatics*, 34(7), 1351–1363.

Mhlanga, D. (2020), Industry 4.0 in finance: the impact of artificial intelligence (AI) on digital financial inclusion, *International Journal of Financial Studies*, 8(3), 1–14.

Milana, C. and Ashta, A. (2021), Artificial intelligence techniques in finance and financial markets: a survey of the literature, *Strategic Change*, 30(3), 189–209.

Milian, E.Z., Spinola, M. de M. and Carvalho, M.M. (2019), Fintech: a literature review and research agenda, *Electronic Commerce Research and Applications*, 34(1), 1–22.

Muthukannan, P., Tan, B., Gozman, D. and Johnson, L. (2020), The emergence of a Fintech Ecosystem: a case study of the Vizag Fintech Valley in India, *Information and Management*, 57(8), 1–39.

Pourhabibi, T., Ong, K.L., Kam, B.H. and Boo, Y.L. (2020), Fraud detection: a systematic literature review of graph-based anomaly detection approaches, *Decision Support Systems*, 133(1), 1–16.

Prentice, C. and Nguyen, M. (2021), Robotic service quality – scale development and validation, *Journal of Retailing and Consumer Services*, 62(1), p. 102.

Pu, R., Teresiene, D., Pieczulis, I., Kong, J. and Yue, X.G. (2021), The interaction between banking sector and financial technology companies: qualitative assessment—a case of lithuania, *Risks*, 9(1), 1–22.

Qadiri, R.M., Shabir, N. and Qadri, M. (2020), Conceptualizing Possibilities of Artificial Intelligence in Furtherance of the Banking Sector: an Effective Tool for Improving Customer Relationship, Customer Service and Public Relations, *International Journal of Finance, Insurance and Risk Management*, 10(2), 44–65.

R, A., Kuanr, A. and KR, S. (2021), Developing banking intelligence in emerging markets: systematic review and agenda, *International Journal of Information Management Data Insights*, 1(2), 1–11.

R., V. and Ravi, H. (2021), Innovation in banking: fusion of artificial intelligence and blockchain, *Asia Pacific Journal of Innovation and Entrepreneurship*, 15(1), 51–61.

Rahman, M., Ming, T. H., Baigh, T. A. and Sarker, M. (2021), Adoption of artificial intelligence in banking services: an empirical analysis, International Journal of Emerging Markets, Emerald insight, Vol. ahead-of-print (No. ahead-of-print).

Raj, A. and Sah, B. (2019), Analyzing critical success factors for implementation of drones in the logistics sector using grey-DEMATEL based approach, *Computers and Industrial Engineering*, 138(1), 1–45.

Ramamurty, V.S., Kumar, T.S. and Nagaraj, P. (2021), Reaping Benefits through Implementing' Artificial Intelligence' applications in Banking Sector, *Natural Volatiles & Essential Oils*, 8(4), 438–445.

Ravikumar, T., Murugan, N., Suhashini, J. and Rajesh, R. (2021), Banking on Artificial Intelligence to Bank the Unbanked, *Annals of RSCB*, 25(5), 129–132.

Rodrigues, A. R. D., Ferreira, F. A. F., Teixeira, F. J. C. S. N., Zopounidis, C. (2022). Artificial intelligence, digital transformation and cybersecurity in the banking sector: A multi-stakeholder cognition-driven framework. Research in International Business and Finance, 60, 101616.

Ryu, H.S. (2018), What makes users willing or hesitant to use Fintech?: the moderating effect of user type, *Industrial Management and Data Systems*, 118 3, 541–569.

Ryzhkova, M., Soboleva, E., Sazonova, A. and Chikov, M. (2020), Consumers' Perception of Artificial Intelligence in Banking Sector, *SHS Web of Conferences*, 80, 010.

Sabharwal, C.L. (2018), The rise of machine learning and robo-advisors in banking, *IDRBT Journal of Banking Technology*, 2(1), 28–43.

Sepehri-Rad, A., Sadjadi, S.J. and Sadi-Nezhad, S. (2019), An application of DEMATEL for transaction authentication in online banking, *International Journal of Data and Network Science*, 3(2), 71–76.

Shaikh, A.A., Alharthi, M.D. and Alamoudi, H.O. (2020), Examining key drivers of consumer experience with (non-financial) digital services—an exploratory study, *Journal of Retailing and Consumer Services*, 55(1),1–10.

Shareef, M.A., Baabdullah, A., Dutta, S., Kumar, V. and Dwivedi, Y.K. (2018), Consumer adoption of mobile banking services: an empirical examination of factors according to adoption stages, *Journal of Retailing and Consumer Services*, 43(1), 54–67.

Sharma, S.K. and Sharma, M. (2019), Examining the role of trust and quality dimensions in the actual usage of mobile banking services: an empirical investigation, *International Journal of Information Management*, 44(1), 65–75.

Shavarani, S. M., Nejad, M. G., Rismanchian, F., & Izbirak, G. (2018), Application of hierarchical facility location problem for optimization of a drone delivery system: a case study of Amazon prime air in the city of San Francisco, *The International Journal of Advanced Manufacturing Technology*, 95(9), 3141-3153.

Singh, S. and Srivastava, R.K. (2018), Predicting the Intention to Use Mobile Banking in India Introduction, *International Journal of Bank Marketing*, 36(2), 357–378.

Sivathanu, B. (2019), Adoption of digital payment systems in the era of demonetization in India: an empirical study, *Journal of Science and Technology Policy Management*,10(1), 143–171.

Subero-Navarro, Á., Pelegrín-Borondo, J., Reinares-Lara, E. and Olarte-Pascual, C. (2022), Proposal for modelling social robot acceptance by retail customers: CAN model + technophobia, *Journal of Retailing and Consumer Services*, 64(1), 1–9.

Tang, S.M. and Tien, H.N. (2020), Impact of Artificial Intelligence on Vietnam Commercial Bank Operations, *International Journal of Social Science and Economics Invention*, 6(07), 296–303.

Tao, R., Su, C.W., Xiao, Y., Dai, K. and Khalid, F. (2021), Robo advisors, algorithmic trading and investment management: Wonders of fourth industrial revolution in financial markets, *Technological Forecasting and Social Change*, 163, p. 120.

Truby, J., Brown, R. and Dahdal, A. (2020), Banking on AI: mandating a proactive approach to AI regulation in the financial sector, *Law and Financial Markets Review*, Taylor & Francis, 14(2), 110–120.

Vafadarnikjoo, A., Mobin, M., Allahi, S. and Rastegari, A. (2015), A hybrid approach of intuitionistic fuzzy set theory and dematel method to prioritize selection Criteria of bank branch's locations, *International Annual Conference of the American Society for Engineering Management*, 595–604.

Valmohammadi, C. and Dashti, S. (2016), Using interpretive structural modelling and fuzzy analytical process to identify and prioritize the interactive barriers of e-commerce implementation, *Information and Management*, 53(2), 157–168.

Wang, X., Sadiq, R., Khan, T.M. and Wang, R. (2021), Industry 4.0 and intellectual capital in the age of FinTech, *Technological Forecasting and Social Change*, 166(1), 1–22.

Wang, Y., Xiuping, S., Zhang, Q. (2021). Can fintech improve the efficiency of commercial banks? — An analysis based on big data. Research in International Business and Finance, 55, 101338.

Yadav, A. (2021), How Artificial Intelligence is Transforming the Banking Industry: Data Analysis Review, *International Journal of Advanced Research in Science, Communication and Technology*, 7(2), 76–81.

Yazdi, M., Khan, F., Abbassi, R. and Rusli, R. (2020), Improved DEMATEL methodology for effective safety management decision-making, *Safety Science*, 127(1), 1–17.

Yüksel, S., Dinçer, H. and Emir, Ş. (2017), Comparing the performance of Turkish deposit banks by using DEMATEL, Grey Relational Analysis (GRA) and MOORA approaches, *World Journal of Applied Economics*, 3(2), 26–47.

Zhao, Q., Tsai, P.H. and Wang, J.L. (2019), Improving financial service innovation strategies for enhancing China's banking industry competitive advantage during the fintech revolution: a hybrid MCDM model, *Sustainability (Switzerland)*, 11(5), 1–2.