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# Analysis of barriers to AI banking chatbot adoption in India: An ISM and MICMAC approach

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## Abstract

Chatbots are becoming popular in the rapidly developing field of Artificial Intelligence (AI) to facilitate more effective communication between businesses and customers. AI-powered banking chatbots are gaining popularity and present novel opportunities to provide 24/7 front-line support and customised banking assistance. Despite these advantages, banking chatbots are not widely used and have not been adopted as customer service in Indian banks. This research paper explores the obstacles associated with the widespread adoption of banking chatbots in the financial landscape. As disruptive technologies like Artificial Intelligence and Natural Language Processing (NLP) continue to reshape the banking industry globally, understanding the specific barriers to chatbot integration becomes imperative. The current research contributes to the AI discipline by holistically examining the barriers to banking chatbot adoption in India using the Interpretive Structural Modelling (ISM) methodology. The study employs a three-step approach by identifying key barriers to adopting banking chatbots through an extensive literature review and experts' opinions. Then, the Interpretive Structural Modelling (ISM) methodology creates a hierarchical model. For this, data is collected from subject matter experts to develop the interpretive model. Thirdly, MICMAC analysis is conducted to classify and sort the corresponding variables based on their driving and dependence power. The analysis reveals that the absence of AI guidelines, lack of human touch and lack of audibility and transparency of AI systems are some of the critical barriers to the deployment of AI banking chatbots, requiring special focus to streamline the regulatory framework and anthropomorphic features of AI chatbot for successful implementation and deployment. Recommendations for practitioners and other stakeholders and research limitations are also discussed.

**Keywords:** Artificial Intelligence, Barriers, AI Banking Chatbot, Interpretive Structural Modeling (ISM), Structured self-interaction matrix (SSIM), MICMAC

## Introduction

In the rapidly evolving landscape of the financial services industry, the integration of advanced technologies has become pivotal for maintaining competitiveness and enhancing customer experiences (Dwivedi et al., 2021). Adding to this, the COVID-19 epidemic has also caused a significant change in the way individuals and communities interact and function. With its burgeoning population and rapidly digitising economy, India presents a fertile ground for technological innovations in the financial domain. This widespread adoption of disruptive digital technologies has taken place in the banking sector, leading to a radical shift in banking operations for enhancing customer experience and handling information and services (Agrawal et al., 2024). A progressively prevalent and noteworthy technical advancement in the banking industry is using AI-powered chatbots (Richad et al., 2019). A chatbot is a computer programme that communicates with users in natural language, either orally or through text, assesses their needs, and responds to the organisation's policies and data (Bialkova, 2023). Chatbots will save banks billions of dollars over the next ten years. As per a report published by Juniper, by 2022, chatbots will save over $8 billion in annual costs. At least 85% of customer service conversations will be handled by chatbots by 2020, predicts Gartner. Banks can employ chatbots as an effective way to improve customer interactions, which can enhance service quality, establish solidarity between the bank and the customer, and improve the customer experience. While the promise of banking chatbots lies in their ability to streamline customer interactions, provide real-time assistance, and reduce operational costs, their adoption in the Indian context is far from seamless (Lappeman et al., 2023; Hsu et al., 2023). The widespread adoption of banking chatbots faces many challenges, particularly in diverse and dynamic markets such as India. Hence, understanding and addressing the potential difficulties that the Indian banking sector may encounter in adopting chatbot technologies is essential for unleashing their full potential and realising the envisioned benefits.

**Motivation for the study**

India is a fast-developing economy; therefore, the banking sector must implement AI technologies to enhance operations. Implementing AI chatbots still faces obstacles in the Indian banking sector (Gupta & Sharma, 2019; Rani et al., 2023; Hari et al., 2022). Although limited studies have examined attitudinal, psychological, and motivational elements influencing consumers' likelihood to adopt new information technology developments, relatively few have examined the difficulties associated with implementing them (Dwivedi et al., 2021). Also, whereas earlier studies have utilised statistical techniques, such as Structural Equation Modelling (SEM) (Mishra et al., 2022) or Total Interpretive Structural Equation Modelling (TISM) (Kar et al., 2021) or regression (Setyawan et al., 2018), the current study leverages the ISM approach. ISM integrates qualitative and quantitative techniques to rank (Nguyen et al., 2021; Agrawal et al., 2024) the various financial, technical, regulatory, and customer-related barriers and underlying sub-barriers. Current research prioritises the barriers to chatbot adoption and deployment in the Indian banking industry. Research is needed to accelerate the adoption and implementation of banking chatbots in India. The current study will contribute to the academic discourse on technology adoption in emerging financial markets and serve as a practical guide for industry stakeholders, policymakers, and banking institutions seeking to navigate the intricate terrain of chatbot integration. Ultimately, understanding and fostering the barriers to banking chatbot adoption in India will pave the way for strategic initiatives to foster a symbiotic relationship between technology and the Indian banking ecosystem.

The research gap highlighted above is the primary motivating factor for the current work, as the adoption of chatbots is critical to the growth of the banking industry. To address the gaps in the area, the following important research questions have been identified:

RQ1. To identify the factors creating barriers to AI banking chatbot adoption in India.

RQ2. To analyse the interrelationships among these identified factors and prioritise (using ISM and MICMAC)

RQ3. To develop a framework of the relationships between the contextual variables

This paper first provides a literature review of the adoption of banking chatbots in India. Next, we present our research methodology and rationale, followed by the results, analysis, and discussions. Lastly, the implications for academia and practitioners are reported, followed by the conclusion, limitations, and potential future work ideas.

## Literature review

The landscape of banking services has undergone a transformative shift with the advent of chatbot technology (Richad et al., 2019; Hasan et al., 2023). Scholars have extensively explored the transformative potential of chatbots in enhancing customer engagement, improving operational efficiency, and streamlining banking services (Hari et al., 2022; Mulyono & Sfenrianto, 2022; Trivedi, 2019). Notably, seminal works by Pillai & Sivathanu (2020) and Sheehan et al. (2020) provide comprehensive insights into the global landscape of chatbot adoption, emphasising technology's pivotal role in reshaping customer interactions. However, there are a few challenges to chatbot adoption within the banking industry in India, namely, issues around security, privacy, trust, and the workforce being replaced by machines (Lappeman et al., 2023; Alagarsamy & Mehrolia, 2023; Patil & Kulkarni, 2019). Similarly, robust IT infrastructure, data security measures and organisational adaptability are highlighted as solid factors for the effective integration of AI in banking organisations (Hasan et al., 2023; Rani et al., 2023). For fast-developing countries like India, an increasing amount of research is being done to get a holistic view of all the barriers the banking industry faces while using banking chatbots.

While earlier studies have examined chatbot adoption in developed countries (Belanche et al., 2019; Jang et al., 2021), there is a shortage of literature on analysing the barriers related to chatbot adoption in the Indian banking industry. Previous literature focussed on few of these challenges like execution and implementation costs (Hwang & Kim, 2021; Caldarini et al., 2022), deficiency of skilled workers (Nguyen et al., 2019; Zhang et al., 2023), security issues (Hasal et al., 2021; Hardi et al., 2020), the challenges of accomplishing a suitable adjustment between automation and human intervention (Suhel et al., 2020), cross-language compatibility (Rustamov et al., 2021), and the absence of industry regulations and standardised guidelines (Agrawal et al., 2024; Mogaji et al., 2021). Besides, previous literature highlights a few customer-related, technical, and sociocultural issues as critical barriers (Hari et al., 2022; Mogaji et al., 2021; Fernandes & Oliveira, 2021). Cultural preferences and lack of digital literacy among various population groups are also highlighted as essential factors impacting chatbot deployment within the Indian keeping banking industry (Abdulquadri et al. (2021). Furthermore, past studies demonstrate that the key components driving banking chatbot adoption are clients' trust and concerns around AI-based communications (Alagarsamy & Mehrolia, 2023; Patil & Kulkarni, 2019). However, these barriers have never been examined extensively in developing countries like India. Research done by Yasir et al. (2022) states that the acceptance and deployment of banking chatbots generate a dynamic environment where many barriers interrelate and impact each other. This makes it essential to examine each of these barriers individually and holistically. With the dynamic nature of the financial landscape in India, characterised by rapid technological advancements and evolving consumer behaviours, the current research aims to contribute holistically to the existing literature by examining the barriers to banking chatbot adoption in India.

In the current research, the variables (barrier factors) were developed based on a comprehensive review of existing literature pertaining to AI chatbot adoption in the banking sector in India. This literature review provided us with a robust foundation for identifying and selecting the key barrier factors. Table 1 lists references from the literature for each of the identified barrier. Following the literature review and input from industry experts, the study has identified a total of twelve (12) barriers, divided into four main categories - Financial, customer-related, technical, and regulatory. All the barriers and sub-barriers are presented in Table 1, along with their descriptions and code.

**Table 1. Barriers and sub-barriers to AI banking chatbot adoption in India**

| S.No. | Barrier | Sub-Barrier | Description | Reference |
|---|---|---|---|---|
| 1 | Financial Barriers | Initial setup cost (B1) | These are first-time costs and include the acquisition of chatbot software or platforms, customisation and integration with existing systems, staff training, and initial infrastructure setup. | Caldarini et al. (2022); Hwang & Kim (2021) |
| | | Ongoing maintenance expenses (B2) | Ongoing maintenance involves regular enhancements and improvements to keep pace with evolving customer needs and technological advancements. | Singh et al. (2019); Toprak et al. (2023) |
| | | Uncertain return on investment (B3) | It refers to the ambiguity or unpredictability related to the financial benefits that banks face by investing in a banking chatbot, as the returns on initial investment are difficult to quantify in this case. | Raval, H. (2020); Janssen et al. (2021) |
| 2 | Customer related barriers | Privacy and security issues (B4) | It pertains to concerns regarding the protection of sensitive customer information and safeguarding against unauthorised access or data breaches. | Cardona et al. (2021); Kim et al. (2023); Patil & Kulkarni (2019) |
| | | Lack of trust (B5) | Customers hesitate to engage with chatbots for fear of errors, misinformation, or potential data breaches, leading to a reluctance to adopt this technology for their banking needs. | Lappeman et al. (2023); Nordheim et al. (2019); Hildebrand & Bergner (2021); Følstad et al. (2018) |
| | | Lack of awareness and digital skills (B6) | It refers to the limited knowledge and proficiency among customers in using digital tools and platforms, including banking chatbots. | Abdulquadri et al. (2021); Alt et al. (2021) |
| 3 | Technical barriers | Need for multilingual support (B7) | Banking chatbots are required to effectively communicate with customers in multiple languages to accommodate diverse linguistic preferences and demographics. | Rustamov et al. (2021); Mogaji et al. (2021); Gain et al. (2022) |

| | | | | |
|---|---|---|---|---|
| | | Limitations in N.L.P. (B8) | These are the hurdles that banking chatbots encounter when trying to understand and respond to human language. These challenges stem from the complexity of accurately interpreting various linguistic nuances, contexts, and intentions. | Tanveer et al. (2023); Janssen et al. (2021); Suhel et al. (2020) |
| | | Lack of human touch (B9) | It refers to the difficulty banking chatbots face in replicating the warmth, empathy, and personalised assistance often provided by human customer service representatives. | Sheehan et al. (2020). Balakrishnan et al. (2020); Go & Sundar (2019) |
| 4 | Regulatory barriers | Auditability and Transparency of A.I. Systems (B10) | There's a difficulty in understanding how banking chatbots operate and make decisions. Chatbots don't explain how they work clearly, making it challenging for users to trust and adopt them. | Lappeman et al. (2023); Hasan et al. (2023) |
| | | Stringent financial regulatory compliances (B11) | These are strict rules and standards that banks must follow to ensure compliance with financial regulations and laws to protect customers, prevent fraud, and maintain the stability of the economic system. | Tanveer et al. (2023). Rahmani & Zohuri (2023). Butler & O'Brien (2019) |
| | | Absence of A.I. Guidelines (B12) | It refers to the lack of clear regulations or standards specifically tailored to govern the use of artificial intelligence (A.I.) in banking operations to facilitate the responsible and ethical deployment of A.I. technologies in banks. | Agrawal et al. (2024); Mogaji et al. (2021); Dewasiri et al. (2024) |

## Research Methodology

The research employed a three-step methodology: (1) Carrying out a review of existing literature and consulting with experts to identify barriers to the adoption of AI banking chatbots; (2) Creating the ISM model to analyse the intricate and hierarchical relationships among identified barriers; and (3) Applying MICMAC analysis for determining each factor's driving and dependence power.

The choice of Interpretive Structural Modeling (ISM) as the methodology for this analysis stems from its suitability for handling complex decision-making problems with multiple criteria. By structuring the barriers into categories and sub-categories, ISM allows for a systematic evaluation of their relative importance, providing a nuanced understanding of their impact on the adoption process. This methodological approach empowers decision-makers to make informed choices and interventions based on the specific challenges prevalent in the Indian banking landscape. In the current research, the variables (barrier factors) were developed based on a comprehensive review of existing literature pertaining to AI chatbot adoption in the banking sector in India. This literature review provided us with a robust foundation for identifying and selecting the key barrier factor barriers. Table 1 lists references from the literature for each of the identified barrier. Additionally, to ensure the validity and relevance of these factors experienced domain experts were consulted, who provided valuable insights and feedback on the initial selection. Regarding the relationships among these variables, the current research employed the Interpretive Structural Modeling (ISM) methodology. ISM facilitated the establishment of contextual relationships among every pair of identified barrier factors. This method helped in creating a hierarchical model that clearly illustrates the dependencies and interactions among the variables, thus offering a clear understanding of how and why these barriers influence each other within the context of AI chatbot adoption in Indian banking. Fig. 1 defines the development and selection process of the variables (barriers) for the current research.

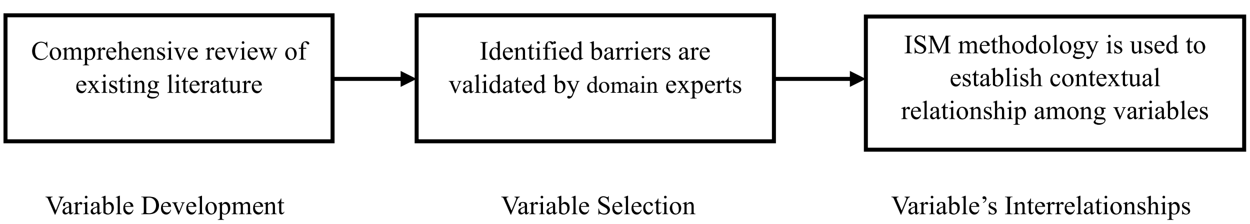



**Fig. 1. Development and selection process of barriers**

The research categorises barriers into key dimensions that encapsulate the major impediments to chatbot adoption: financial, customer-related, technical, and regulatory. Sub-barriers such as uncertain return on investment, lack of trust, limitations in NLP, regulatory issues, and others are broken down within each barrier category to provide a thorough understanding of the challenges that banking chatbots in India face. Based on a review of existing literature and expert opinion, the current study identifies the barriers to AI banking chatbot adoption. To show the interrelationships and associations between the barriers, pairwise comparisons of the identified barriers were conducted to get expert opinions. ISM methodology does not rely on large sample sizes typical of statistical analyses. Instead, it focuses on qualitative assessments and expert judgment to establish contextual relationships among variables. While the primary goal of ISM is not statistical inference, the insights gained from our expert panel were invaluable in identifying the interdependencies among barrier factors, thereby offering meaningful contributions to both theory and practice in the field.

As per the existing literature, the minimum number of domain experts can be 2 for conducting ISM (Ravi and Shankar, 2005; Mathiyazhagan et al., 2013). Also, according to Janes (1988), the average number of experts for ISM methodology is 8. Current study involves 10 domain experts from industry and academia, each having experience of 15-20 years. These experts were carefully selected based on their expertise and experience in the domain of AI chatbot adoption and banking operations in India. These domain experts provided informed opinions and insights that were critical in constructing the ISM model and determining the contextual relationships among the identified barrier factors. Including such highly expert respondents increases and ensures the reliability of the study.

Further details about these experts are provided in Table 2. After interviewing all the experts, feedback from all the experts was assembled to produce the structural self-interaction matrix (SSIM). ISM methodology and MICMAC analysis are explained in detail in the subsequent sections.

**Table 2. Profile of Experts**

| Expert | Industry/ Academia | Expert profile (role) | Total experience (years) | Qualification | Place |
|---|---|---|---|---|---|
| Expert 1 | Industry | Vice President, Finance Dept., Banking | >15 | MBA | Gurgaon |
| Expert 2 | Industry | Vice President, IT Dept., Banking | >16 | MTech | Mumbai |
| Expert 3 | Academia | Assistant Professor- Banking & Finance | >17 | PhD | Delhi |
| Expert 4 | Industry | Practice Leader, AI & Analytics | >18 | BTech, MBA | Gurgaon |
| Expert 5 | Industry | Head of Digital Banking | >15 | BTech, PhD | Pune |
| Expert 6 | Industry | Product Manager for Digital Solutions | >14 | BTech | Hyderabad |
| Expert 7 | Academia | Associate Professor- AI & ML | >20 | MBA, PhD | Noida |

| | | | | | |
|---|---|---|---|---|---|
| Expert 8 | Industry | Compliance Officer, Banking | >20 | LLB, MBA | Gurgaon |
| Expert 9 | Academia | Assistant Professor-IT | >15 | MBA | Bangalore |
| Expert 10 | Industry | Product Manager for AI Solutions | >15 | MTech | Chennai |

**Interpretive Structural Modeling (ISM)**

Interpretive structural modelling (ISM) is a crucial multicriteria decision-making method for analysing difficult situations and interconnected relationships (Warfield, 1973; Attri et al., 2020). It is a qualitative method that transforms complicated models into clear conceptual models that outline how factors are related (Gupta & Sahu, 2013; Sushil, 2012). The final model precisely illustrates a clear structure and assists by offering a solution for the given challenge (Sindhu et al., 2016). ISM technique has been used in several domains of management and other social science research-related fields (Khan & Haleem, 2012; Thakur & Wilson, 2024; Janssen et al., 2021; Valmohammadi & Dashti, 2016; Gan et al., 2018; Kumar et al., 2021; Kar et al., 2021; Saka & Chan, 2020; Choudhary et al., 2022; Kaur et al., 2022).
ISM can capture more dynamic and complicated problems than other methods of multiple criteria decision-making strategies (Liou & Tzeng, 2012). Table 3 lists a few of the reference studies that employ ISM to examine different barriers and drivers related to the application of AI in several industries/domains.

**Table 3. Reference studies using ISM to examine barriers related to AI application in different domains.**

| Context | Domain | Reference |
|---|---|---|
| The positive effects of Automation and AI in the AEC Industry: A Framework for Interpretive Structural Modelling | Architecture, engineering, and construction (AEC) | Onososen & Musonda (2022) |
| An interpretive structural model for algorithmic judgements in fraud detection using artificial intelligence | Industry 4.0 | Tan et al. (2023) |
| Healthcare is changing because of AI in the COVID-19 era: An overview of prognostic factors and diagnosis. | Healthcare | Saha et al. (2021) |
| ISM and MICMAC Modelling Approach: An analytical evaluation of Artificial Intelligence enablers boosting business intelligence in the Indian banking sector | Indian banks | Shekhar, S. (2022) |
| | Conversational agents | |

| | | |
|---|---|---|
| ISM and MICMAC analysis to model the main drivers and obstacles to the deployment of AI-based conversational interfaces | Cloud system | Choudhary et al. (2022) |
| Analysis of the key variables for developing a sustainable AI cloud system in an IT industry using integrated MCDM technique - AHP-ISM-MICMAC | Climate change | Yenugula et al. (2023) |
| AI's role in combating climate change: Modelling energy sector barriers using an ISM approach | Manufacturing & Industrial Sector | Mohammed et al. (2023) |
| Industrial and manufacturing sectors' Use of IoT, Big Data, and AI During the COVID-19 pandemic: An ISM approach | | Deka et al. (2024) |

The literature reported steps for ISM methodology (Kannan et al., 2009) is as follows:

Step 1: Identify barriers from existing literature and consult with domain experts.
Step 2: Creation of a structural self-interaction matrix (SSIM) for all the identified barriers.
Step 3: Create the Initial reachability matrix (IRM) and the Final reachability matrix (FRM) by applying the transitivity rule.
Step 4: The FRM is portioned into various levels using multiple iterations.
Step 5: Creation of a digraph based on inter-relationships listed in FRM.
Step 6: The final ISM model is designed by swapping out the nodes with variable names.

The methodology followed in this study is presented in Fig. 2.

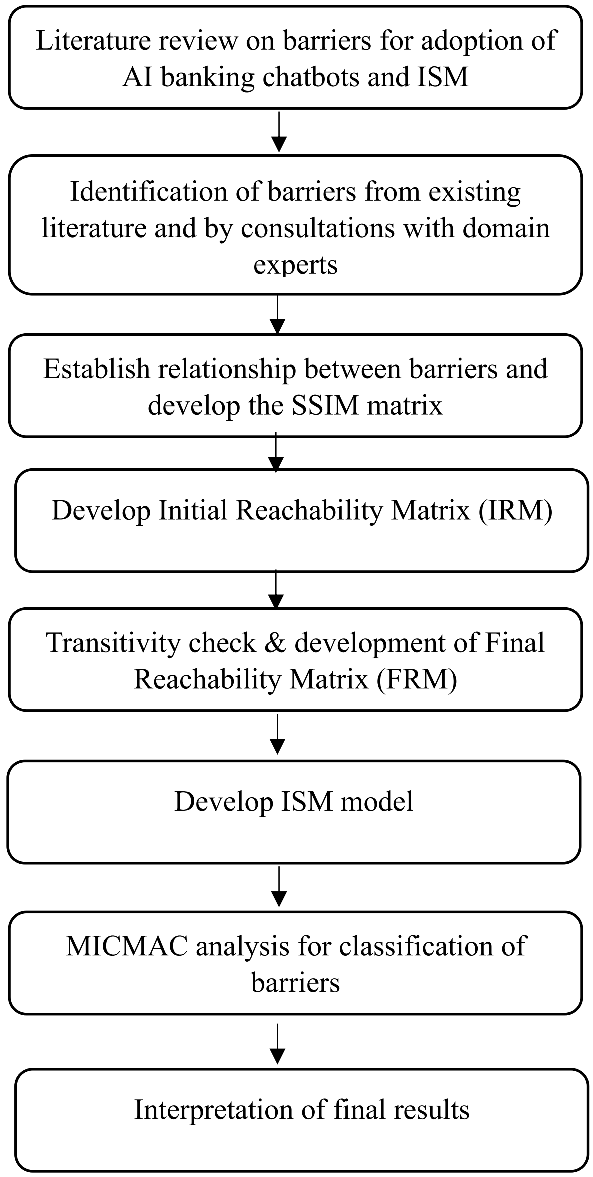



**Fig. 2. Steps in ISM Methodology**

**MICMAC Analysis**

After identifying the barrier components, we analysed and categorised the dependencies between the barriers using MICMAC analysis. This technique uses a reachable matrix to calculate the driving forces and dependencies in the ISM model, allowing for a more thorough examination (Sharma & Bumb, 2021;

Nandal et al., 2019). This strategy makes a greater comprehension of the mechanism and scope of risk factor interactions possible.

## Results and Discussion

### Development of Structured Self-Interaction Matrix (SSIM)

Based on the barriers identified in the previous stage, a contextual relationship is built for every pair of barriers. SSIM matrix demonstrating the interactions among all barriers impeding the adoption of AI banking chatbots in India is created using pairwise contextual connections.
Academicians and banking sector experts were consulted (Table 2) to establish and represent the relationship between two barriers (i and j) using symbols V, A, X, and O, where-
V - Barrier j is impacted by Barrier i.
A - Barrier i will be impacted by Barrier j.
X - Both barriers i and j will impact each other.
O - Barriers i and j are not related and don't impact each other
Table 4 presents the SSIM matrix created using the above notations.

**Table 4. Structural self-interaction matrix (SSIM)**

| **Barrier j →** | **B12** | **B11** | **B10** | **B9** | **B8** | **B7** | **B6** | **B5** | **B4** | **B3** | **B2** | **B1** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Barrier i ↓** | | | | | | | | | | | | |
| **B1: Initial setup cost** | O | O | O | O | O | O | O | O | O | O | O | - |
| **B2: Ongoing maintenance expenses** | O | O | O | O | O | O | O | O | O | O | - | |
| **B3: Uncertain return on investment** | A | O | O | O | A | O | A | A | A | - | | |
| **B4: Privacy and security issues** | O | O | A | O | O | O | O | O | - | | | |
| **B5: Lack of trust** | A | O | A | A | A | O | X | - | | | | |
| **B6: Lack of awareness and digital skills** | O | O | O | O | O | O | - | | | | | |
| **B7: Need for Multilingual Support** | O | O | O | O | O | - | | | | | | |
| **B8: Limitations in NLP** | O | O | O | O | - | | | | | | | |
| **B9: Lack of human touch** | O | O | X | - | | | | | | | | |
| **B10: Lack of Auditability and Transparency of AI Systems** | A | O | - | | | | | | | | | |
| **B11: Strict financial regulatory compliances** | O | - | | | | | | | | | | |
| **B12: Absence of AI guidelines** | - | | | | | | | | | | | |

**Development of Reachability Matrix (RM)**

The process begins with the development of the initial reachability matrix (IRM), given in Table 5, from which the final reachability matrix (FRM) is derived. For this, the initial reachability matrix (IRM) was derived from the SSIM matrix by following the rules mentioned below:

1. If the value of the (i,j) cell in the SSI matrix is symbol V, then the value of cells (i,j) and (j,i) of the initial reachability matrix becomes 1 and 0 respectively,
2. If the value of (i,j) cell in SSI matrix is symbol A, then the value of cells (i,j) and (j,i) of the initial reachability matrix becomes 0 and 1, respectively;
3. If the value of the (i,j) cell in the SSI matrix is symbol X, then the value of both the cells (i,j) and (j,i) of the initial reachability matrix becomes one and ;
4. If the value of the (i,j) cell in the SSI matrix is symbol O, then the value of both the cells (i,j) and (j,i) of the initial reachability matrix becomes 0.

Then, in the next step, the FRM (given in Table 6) is derived from the IRM by following the transitivity rule given by Kannan et al. (2014). According to this rule, if variable "a" is related to variable "b" and variable "b" is related to variable "c", then variable "a" will be necessarily related to variable "c".

**Table 5. Initial reachability matrix (IRM)**

| Barriers | B12 | B11 | B10 | B9 | B8 | B7 | B6 | B5 | B4 | B3 | B2 | B1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| B1: Initial setup cost | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| B2: Ongoing maintenance expenses | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| B3: Uncertain return on investment | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| B4: Privacy and security issues | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| B5: Lack of trust | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| B6: Lack of awareness and digital skills | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| B7: Need for Multilingual Support | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| B8: Limitations in NLP | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| B9: Balancing automation with human intervention | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 0 |
| B10: Lack of Auditability and Transparency of AI Systems | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 0 |
| B11: Stringent financial regulatory compliances | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| B12: Absence of AI guidelines | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 1 |

**Table 6. Final reachability matrix (FRM)**

| Barriers | B12 | B11 | B10 | B9 | B8 | B7 | B6 | B5 | B4 | B3 | B2 | B1 | Driving Power |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| B1: Initial setup cost | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| B2: Ongoing maintenance expenses | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| B3: Uncertain return on investment | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| B4: Privacy and security issues | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 |
| B5: Lack of trust | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 3 |
| B6: Lack of awareness and digital skills | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 3 |
| B7: Need for multilingual Support | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 |
| B8: Limitations in NLP | 0 | 0 | 1 | 0 | 1 | 1* | 0 | 1 | 0 | 0 | 0 | 0 | 4 |
| B9: Balancing automation with human intervention | 0 | 0 | 1* | 1* | 1 | 1* | 0 | 0 | 1 | 1 | 0 | 0 | 6 |
| B10: Lack of Auditability and Transparency of AI Systems | 0 | 0 | 1* | 1 | 1 | 1* | 0 | 0 | 1 | 1 | 0 | 0 | 6 |
| B11: Stringent financial regulatory compliances | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 |
| B12: Absence of AI guidelines | 0 | 0 | 1 | 1* | 1 | 1* | 0 | 0 | 1* | 1 | 0 | 1 | 7 |
| **Dependence Power** | 1 | 1 | 8 | 4 | 6 | 6 | 1 | 1 | 3 | 3 | 1 | 1 | |

**Level Partitioning (LP)**

Level partitioning aids in the creation of the hierarchical structure of variables under study (Warfield, 1973). By organising elements into hierarchical levels, LP provides clarity in analysing complex interrelationships and dependencies within the system. It also helps decision-makers identify critical elements that have significant influence over others and need prioritisation in terms of management, resource allocation, or intervention. From the final reachability matrix, the reachability and antecedent set for each barrier are obtained (Warfield, 1974). A variable's reachability set consists of the variable itself and the other variables which it may help achieve. Similarly, the antecedent set consists of the variable itself and the other variables that may help achieve them. From these reachability sets and antecedent sets, the intersection sets are also obtained for each variable. Those variables for which the reachability and the intersection sets are the same occupy the top level of the ISM hierarchical model. The top-tier variable wouldn't help with any other variable's achievement outside of its own level. As a result, this top-tier element is identified, made distinct from the other variables, and placed apart. Similarly, the successive top-tier variables are identified for the next levels. In this study, the reachability set, antecedent set, intersection set and levels of all 12 identified barriers are presented in Table 7. These recognised levels assist in creating the digraph and the final ISM model.

**Table 7. Partitioning of barriers to AI banking chatbot adoption in India**

| Barriers | Reachability Set | Antecedent Set A | Intersection Set | Level |
|---|---|---|---|---|
| B1 | 1 | 1 | 1 | 1 |
| B2 | 2 | 2 | 2 | 1 |
| B3 | 3 | 3, 4, 5, 6, 8, 9, 10, 12 | 3 | 1 |
| B4 | 4 | 4, 9, 10, 12 | 4 | 2 |
| B5 | 5, 6 | 5, 6, 8, 9, 10, 12 | 5, 6 | 2 |
| B6 | 5, 6 | 5, 6, 8, 9, 10, 12 | 5, 6 | 2 |
| B7 | 7 | 7 | 7 | 1 |
| B8 | 8 | 8 | 8 | 3 |
| B9 | 9, 10 | 9, 10, 12 | 9, 10 | 3 |
| B10 | 9, 10 | 9, 10, 12 | 9, 10 | 3 |
| B11 | 11 | 11 | 11 | 1 |
| B12 | 12 | 12 | 12 | 4 |

**Formation of ISM based model**

From the final reachability matrix, the digraph and structural model are generated and are given in Fig. 3 and Fig. 4 respectively. A digraph provides a clear visual representation of the directional relationships between elements and shows which elements influence others, making the complex interdependencies easier to understand. Also, by structuring the problem into different levels, the structural model helps in breaking down complex problems into manageable parts, representing all the elements and their interactions. This thorough understanding is crucial for developing robust and effective strategies. The current study uses ISM methodology to develop the diagraph and final structural model to examine the barriers to banking chatbot adoption in India holistically. There is a lacuna for such model development and research in the above area. Fig. 3 represents the contextual relationships among the barriers to AI banking chatbot adoption in India. The structural model is to be prepared using the level partitions while discarding the transitivities, as explained in the ISM methodology (Patil & Warkhedkar, 2016). Four levels of barriers derived from the level partition iteration process are positioned in this model. The barriers at the bottom level are strong influencers in the system. As can be seen from the model, the absence of AI guidelines is the most significant or root or basic barrier to the adoption of AI chatbots in Indian banks. It is evident from the model that the lack of human touch and lack of audibility and transparency of AI systems may be caused by the absence of AI guidelines for AI banking chatbot adoption in India. This lack of human touch and lack of audibility and transparency of AI systems, along with limitations in NLP, may lead to other challenges like privacy and security issues, lack of trust and lack of awareness and digital skills, further resulting in an uncertain return on investment for the banking sector.

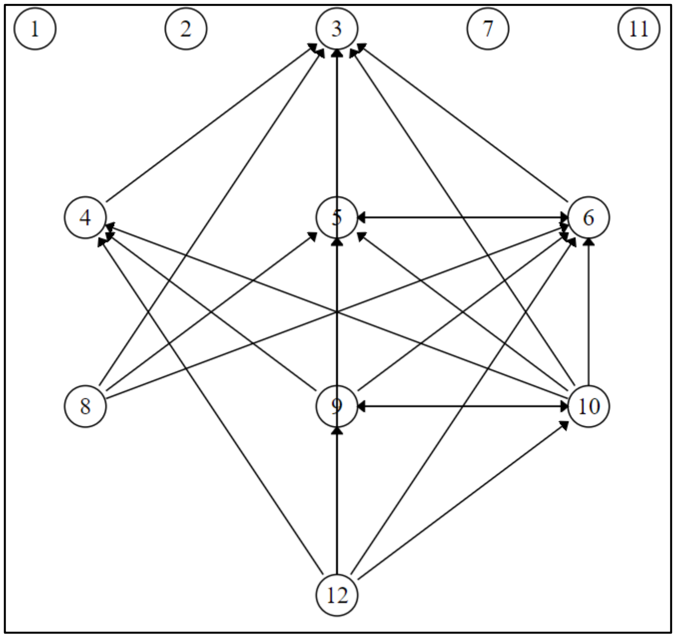



**Fig. 3 Digraph of barriers to AI banking chatbot adoption in India**

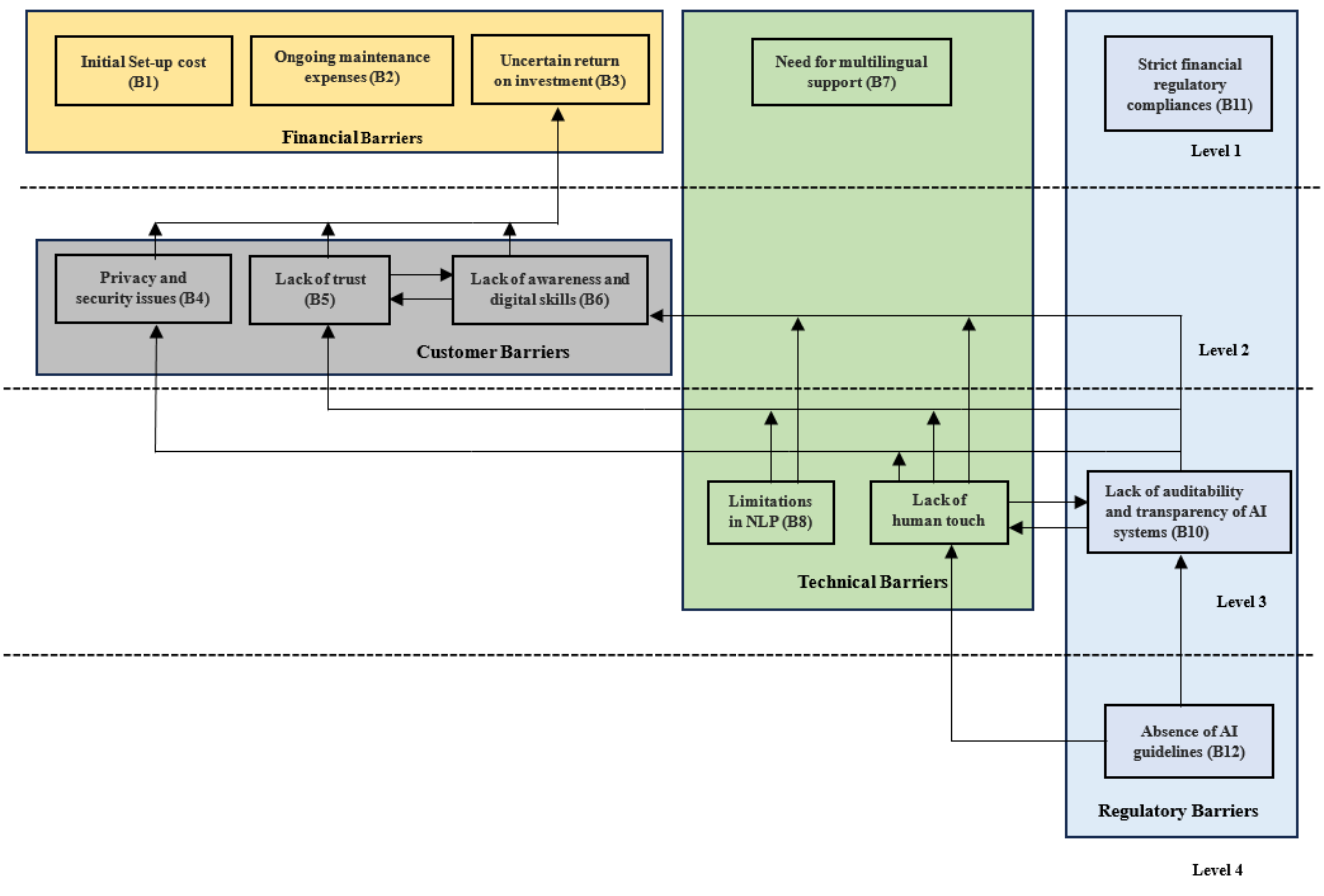
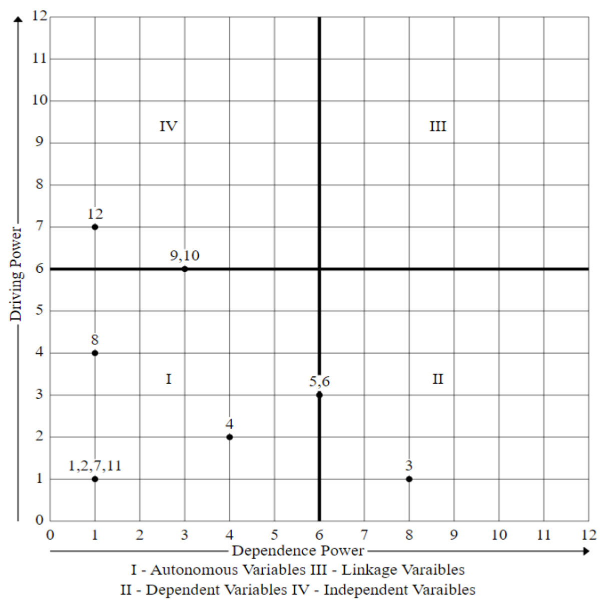


**Fig. 4 ISM-based hierarchical model for barriers to AI banking chatbot adoption in India**

**Results of MICMAC Analysis**

By using the MICMAC analysis, the driving and dependence power of various components within the framework of ISM can be found. This will aid in determining the most important variables influencing the adoption of banking chatbots and in developing the most efficient banking solutions. In the final reachability matrix, the sum of 1s in the given row represents the driving power, and the sum of 1s in the given column represents the dependence power of the variables under consideration. Based on the results of the ISM and MICMAC diagram analysis, it was found that twelve elements were divided into 4 (four) quadrants (Fig. 5).

1) The first quadrant contains 'autonomous barriers', which have weak driving and weak dependence power. Barriers like initial set-up cost (B1), ongoing maintenance expenses (B2), privacy and security issues (B4), need for multilingual support (B7), limitations in NLP (B8) and strict financial regulatory compliances (B11) fall in this quadrant.
2) The second quadrant indicates ***'dependent barriers',*** which show weak driving but strong dependence power. Barrier– uncertain return on investment (B3) falls in this cluster.
3) The third quadrant signifies ***'linkage barriers',*** which have strong driving and dependence power. No such barriers are present in this study.
4) The fourth quadrant contains ***'independent barriers'*** having strong driving power but weak




dependence power. In this quadrant, there are three barriers: lack of AI guidelines, a lack of human touch, auditability, and transparency of AI systems.

**Fig. 5 MICMAC Analysis of barriers**

## Implications of the study

The research study has several significant implications not only for academicians and research scholars but also for practising managers involved in designing and deploying AI chatbots in Indian banks, as discussed below:

### Implications for Academia

The findings of this research hold significant implications for academicians and researchers, particularly in the field of chatbot adoption in banking and other industries. By employing an integrated ISM and MICMAC approach, this study provides a methodological framework that can be applied across various domains to understand the complexities of adoption barriers within dynamic systems. Also, academics can leverage this framework to conduct further research into the adoption of emerging technologies beyond banking chatbots, thereby advancing the understanding of adoption challenges and strategies in diverse contexts.

### Implications for practitioners in the banking sector

This research has many implications for practitioners in the banking industry. By uncovering the hierarchical structure of barriers and the intricate interconnections among them using the ISM and MICMAC approach, this study offers valuable insights that can inform strategic decision-making and intervention planning. Some of the key implications of the study are:

- Significant contribution of the study lies in identifying critical barriers to banking chatbot adoption like lack of human touch, need for multilingual support and limitations in NLP, etc., which have not been explored and studied holistically in the past.
- The research also has several implications as it prioritizes the identified barriers and proposes a structured framework for banks and financial institutions to strategize their efforts to overcome these barriers.
- The study identifies and categorises the barriers in four levels, showing the importance of each barrier in a hierarchical manner. Current study concludes that the absence of AI guidelines (Level 4) is the most important barrier to banking chatbot adoption. This is a major barrier for the Indian government and policymakers to work upon.
- Apart from this, the current research identifies regulatory engagement, industry collaboration, and transparency of AI systems as essential factors for successful deployment of AI chatbots in Indian banks. Banking institutions can utilise these findings to identify priority areas for action and develop targeted strategies to overcome adoption barriers effectively. Policymakers can also benefit from this research by understanding the systemic challenges hindering AI banking chatbot adoption and formulating supportive policies and regulations. Overall, the practical implications of this study enable stakeholders to navigate the complexities of AI banking chatbot adoption more effectively, leading to improved customer experiences and operational efficiencies within the banking sector.

## Conclusion, limitations, and future research scope

The current study assists in identifying multiple barriers associated with banking chatbot adoption in Indian banks. By employing expert opinion and literature review, the ISM methodology develops a hierarchical framework and establishes the relationship among identified barriers. Additionally, classifying the barriers based on their driving and dependence power was made more convenient with the use of MICMAC analysis. The current study identifies and examines 12 barriers related to AI chatbot adoption in Indian banks. According to the study's analysis and findings, limitations in NLP, lack of human touch, lack of trust, privacy, and security issues, need for multilingual support, strict financial regulatory compliances, etc., are few of the major obstacles preventing AI chatbots from being employed by Indian banks.

The key finding of the study is that the absence of AI guidelines is the most important barrier to banking chatbot adoption. The findings reported in the study offer several implications for the Indian government and policymakers in the banking sector. The current study highlights the importance of developing comprehensive AI guidelines tailored to the banking sector in India, encompassing aspects such as data privacy, security, transparency, accountability, and auditability. Further, regulatory engagement, industry collaboration, and transparency of AI systems are found essential for the successful adoption and deployment of chatbot technology in the Indian banking landscape.

There are certain limits to the study despite the numerous scholarly and practical contributions reported. Firstly, the study is limited to the use of chatbots in the Indian banking sector, and as such, to generalise the findings, future research can examine other domains and sectors. Secondly, the ISM model proposed and developed in this study is built upon the opinions of experts. The outcomes of the model analysis may differ in practice, as expert judgements are subject to prejudicial views. As such, Structural equation modelling (SEM), which is a quantitative technique, can be used to statistically validate the findings. Furthermore, the study employs ISM and MICMAC analysis; alternative MCDM techniques, such as AHP, ANP, DEMATEL, and fuzzy FCM, can be used in future research to validate the findings. Furthermore, the focus of the current study is an analysis of the barriers to the adoption of banking chatbots in India. Additional studies should be carried out in other countries and should consider additional aspects like user satisfaction, continuation intention, and post-adoption experience to provide a deeper understanding of users' attitudes towards banking chatbots.

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