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Examining the impediments to AI chatbots adoption among professional practitioners: An ISM – SEM approach

Alaa Amin Abdalla [a], Chandan Kumar Tiwari [b], Mohd. Abass Bhat [b,*], Abhinav Pal [c], Amir A. Abdulmuhsin [d,e]

[a] *Academic Programs for Military Colleges, Abu Dhabi University, Abu Dhabi, United Arab Emirates*
[b] *Business Administration Department, College of Economics and Business Administration, University of Technology and Applied Sciences, Muscat, Oman*
[c] *Symbiosis Centre for Management Studies, NOIDA, Symbiosis International (Deemed University), Pune, India*
[d] *Department of Management Information Systems, College of Administration and Economics, University of Mosul, Mosul, Iraq*
[e] *Department of Management Information Systems, School of Business, The University of Jordan, Jordan*

A R T I C L E I N F O

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A B S T R A C T

This study investigates the barriers to AI chatbot adoption among working professionals, particularly in the accounting and finance sectors. Using a dual-method approach that combines Interpretive Structural Modeling (ISM) and Structural Equation Modeling (SEM), the study identifies and categorizes eight major barriers, emphasizing their interconnected nature and cumulative impact on adoption processes. The findings of this study underline the need of firms implementing a comprehensive strategy that addresses foundational barriers to adoption namely data protection and compliance while also promoting user trust and participation. Finally, this study provides significant insights that can help firms navigate the challenges associated with the AI Chatbot integration, increase operational efficiencies, and improve user experiences.

1. Introduction

In the last few years, the role of Artificial Intelligence has been one of the transformative factors in most sectors; businesses are expected to undergo tremendous change by incorporating AI (Crookes & Conway, 2018). Among the many potential AI applications, AI enhanced chatbots are one of the key technology applications in service-based sectors, such as accounting, finance, healthcare and customer services. These chatbots enable businesses to process and perform fairly programmed and mundane business tasks with high efficiency while improving customer service levels constantly. The list can indeed be endless: helping to streamline workflows, reducing operational costs, helping in decision making, providing real-time support to relieve professionals for more intricate tasks involving human judgment (Gambhir & Bhattacharjee, 2022).

However, despite these promising benefits, there exists a critical concern — Why are these powerful tools not widely adopted in high-stakes domains such as accounting and finance? That leads us to the problem statement: even as AI-driven chatbots enable powerful business benefits, the percentage of working professionals taking advantage of this technology is still relatively small and scattered, especially in the accounting and finance community. This study takes up this paradox to try to understand and explain why a promising AI tool is not adopted at scale in sectors where it promises significant value.

Notwithstanding these promising advantages, working professionals in critical sectors such as accounting and finance were slow to embrace AI-powered chatbots. The slow pace of adaptation might be due to a number of reasons from impediments in technology compatibility with already established systems to human factors, regarding aversion to change and distrust of AI decision. Positioning with their role in ensuring the accuracy, security and regulatory compliance of all financial transactions, it is essential for the accounting and finance professionals to manage this resistance to AI chatbots (Jackson & Allen, 2024).

Previous research has highlighted some of the concerns experts may have with the implementation of AI chatbots: data privacy, regulation issues and the costs of implementation (Ahyar Yuniawan et al., 2025; Bansal et al., 2024; Kelly et al., 2023; Rababah et al., 2022). These issues not only delayed their adoption but also limited how much these chatbots could change those industries worth gains the most. As firms

* Corresponding author.
E-mail addresses: alaa.abdalla@adu.ac.ae (A.A. Abdalla), dr.chandantiwari06@gmail.com (C.K. Tiwari), mohd.abass@utas.edu.om (Mohd.A. Bhat), Abhinav.pal@scmsnoida.ac.in (A. Pal), dr.amir_alnasser@uomosul.edu.iq (A.A. Abdulmuhsin).

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continue to discover how AI can be effectively incorporated into their business processes, it is increasingly crucial for organizations to recognize and address these barriers for technological development as well as business growth (Chavali et al., 2024; Kar et al., 2021). Thus, this research aims to fill a critical gap by identifying and analyzing the key barriers that hinder the integration of AI-based chatbots in professional workflows.

This study has been conducted in India, a rapidly digitizing economy where the adoption of AI-driven tools like chatbots in accounting and finance is growing but still faces significant institutional and technological resistance. Including the Indian context not only adds depth to the analysis but also provides insights that are highly relevant to other emerging economies facing similar adoption challenges. Specifically, this study focuses on the following chatbots: ChatGPT, IBM Watson Assistant, Google Dialogflow, and Microsoft Azure Bot Services, as these represent widely used AI-driven chatbot platforms in finance and accounting domains. By narrowing down the chatbot technologies under study, this research provides targeted and actionable insights rather than generic observations.

Motivated by this consideration, this study looks specifically into the theme of the specific barriers to the adoption of AI chatbots among working professionals, focusing on accounting and finance, because these professions often demand delicate tasks, a lot of accuracy, and reliance on trustable AI systems. Adopting the dual-method approach by combining Interpretive Structural Modeling (ISM) and Structural Equation Modeling (SEM), this study can fully understand these barriers. ISM will help identify and create a hierarchical structure of interrelationships among barriers and develop a hierarchy for further analysis (Warfield, 2003). SEM allows testing these relationships through statistical techniques to evaluate the effects of barriers upon the adoption process (Cheng, 2001). This integrated methodological approach of the study provides insights about the most critical barriers and how they may be appropriately mitigated for the general adoption of AI-based chatbots.

The current study is structured as follows: The next section would present an in-depth review of literature related to some essential concepts and barriers concerning the adoption challenges of AI-based chatbots. Section 3 considers the research methodology: ISM and SEM approaches applied to the study. Section 4 presents the empirical findings of the analysis, and the discussion of the results is given in Section 5. Finally, Section 6 concludes the paper with theoretical and practical implications and Section 7 provides recommendations for future studies.

2. Theoretical background/literature review

2.1. AI-based chatbots: an overview

Several industrial applications have been witnessed to arise with the AI-based chatbots advancing the algorithms of natural language processing and machine learning, which could transform operations, cut costs, and make better decisions (Alkadi & Abed, 2025; Alwageed et al., 2024; Gupta et al., 2025; Panigrahi et al., 2023). Chatbots can automate common tasks like financial reporting and tax filings for accounting and finance (Crookes & Conway, 2018). Despite these advantages, they have not been adopted in a speedy manner because of a set of barriers inhibiting integration into existing professional environments.

2.2. Barriers to AI chatbot adoption

2.2.1. Lack of understanding and awareness

One of the most serious obstacles to AI chatbot adoption is professionals' lack of information and awareness regarding such systems and their value. Many accounting and finance professionals are not fully aware of how AI chatbots can be used, and hence they are less interested in these applications or are even skeptical (Ahyar Yuniawan et al., 2025; Jackson & Allen, 2024; Kar et al., 2021). Professionals will not spend more time and resources to adopt chatbots if the appropriate education or demonstration of the technology's capabilities is not available. In the situation where a training program is nonexistent, employees do not feel prepared to interact with such new technologies (Liu et al., 2024; Singh & Rathi, 2021; Yenugula et al., 2023).

2.2.2. High initial costs

The major adoption barrier is AI-based chatbots will also be a cause of significant upfront cost investments (Rahman et al., 2025; Bansal et al., 2024; Gkinko & Elbanna, 2023). As per Vărzaru (2022a,b), software license, hardware upgrades, and system integration entailed substantial investment, especially for SMEs. In addition, the recurring costs for maintaining the system upgradation also add considerably to the financial burden. While AI chatbots promise enormous long-term cost-saving advantages with automation, the high capital expenditure required in the initial stages is considerable for an organization to be encouraged to adopt the technology (Kar et al., 2021; Raut et al., 2018; Tubadji et al., 2021).

Furthermore, lightweight, open-source AI solutions like neural networks in SciLab demonstrate that cost-efficient character recognition is feasible for SMEs, reducing dependency on expensive proprietary systems. Studies on Artificial Neural Network Based Character Recognition Using SciLab (Darshni et al., 2023) confirm that shallow networks can achieve competitive accuracy with minimal infrastructure, making AI adoption scalable for small businesses. Research further highlights how open-source tools lower barriers to entry, enabling SMEs to implement in-house AI for document processing and automation without high licensing costs (Patel et al., 2023; Zhang et al., 2023). These findings underscore the viability of affordable, scalable AI solutions tailored to budget-constrained enterprises.

2.2.3. Data privacy concerns

Data protection is, no doubt, the most sensitive part in the use of AI chatbots, particularly in the accounting and finance industries. It relates to the processing of huge amounts of secret information, such as personal, financial, and business data (Gkinko & Elbanna, 2023; Zhao et al., 2024). For this reason, data security comes first with utmost costs. AI-based chatbots normally process and store sensitive information, thus raising fears about potential data breaches and unauthorized access (Ahyar Yuniawan et al., 2025; Rababah et al., 2022). Due to this, the organizations fear that AI chatbots would not adhere to them. Such non-adherence would provide the potential legal risks associated with AI chatbots (Kar et al., 2021). Data security breaches could also destroy the trust between clients and organizations, making the latter postpone AI technology adoption unless there are assured robust data protection measures (Brachten et al., 2021).

2.2.4. Regulatory compliance

Another key challenge is that it must address regulatory compliance issues, which go hand in hand with the concerns raised in data privacy. Accountancy and finance professionals largely operate under a very regulated environment wherein severe consequences occur in case any legal and regulatory framework is breached. AI-driven chatbots handle data and decide on automation; therefore, it must be in adherence to strict regulatory requirements such as accurate financial reporting, audit compliance, and tax regulations. The fear of unconscious violation due to AI system usage makes organizations shy away from using chatbots because one mistake in breach leads to reputational loss, fines, and legal cases (Kar et al., 2021; Shakdwipee et al., 2023). In the industrial compliance is a precondition, meeting the full standards of the regulations of the AI systems becomes quite challenging (Kelly et al., 2023).

2.2.5. Technological infrastructure

Organizations do not have the technological infrastructure to support the implementation of AI chatbots (Jackson & Allen, 2024; Vărzaru, 2022b). Most companies are still running old systems that will not support modern AI technologies, hence making the integration of AI chatbots difficult and resource intensive. The need to upgrade the infrastructure, such as increased computing power, cloud services, and data storage capacity, presents overwhelming costs and complexity to the adoption process (Kar et al., 2021). This lack of preparedness in the technological environment acts as a barrier for organizations that might otherwise have gone on to be receptive to the inclusion of AI chatbots (Bansal et al., 2024; Rahman et al., 2025; Raut et al., 2018).

2.2.6. Integration with existing systems

Deploying legacy systems is the reality for most accounting and finance organizations today. Legacy systems do not support the new AI technologies (Almaqtari, 2024; Jackson & Allen, 2024). The interaction of the AI chatbot with these older existing systems is one of the major challenges. As stated by Sreseli (2023), compatibility problems between the AI-driven chatbots and already present software infrastructure can cause inefficiency and, in some instances, break old workflows. The integration of a chatbot with financial management systems, databases, and ERP platforms is complicated and expensive while also leading to some operational disruptions (Almaqtari, 2024). Further, integration issues can impair the ability of the chatbot to operate on data with accuracy, which becomes very significant in such industries where precision is paramount (Tubadji et al., 2021).

2.2.7. Resistance to change

Perhaps the greatest challenge to new technology adoption is resistance to change (Esawe, 2025). In professional services, there are many accounting professionals who have been accustomed to traditional forms and processes and see AI as a necessary disruption. Chavali et al. (2024) further acknowledge that employees often fear job loss due to automation as AI chatbots replace human labor in routine or administrative tasks. This becomes organizational inertia where employees resist new technologies perceived as threats to their roles (Vărzaru, 2022a). Also, even when the technology seems good, many professionals may not be willing to change well-known workflows, further slowing the adoption process (Kar et al., 2021; Yenugula et al., 2023).

2.2.8. Skill gap

The gap in skills related to the proper implementation of Zaidi et al. (2025). As is evident, according to Mohamed Saad (2024), accounting and finance professionals are not technically skilled enough to manage and use systems based on AI appropriately, thus making it quite challenging for adoption as the organization must spend a lot on training and development programs to upscale its workforce (Bansal et al., 2024; Saad et al., 2023) Without adequate training, the employees may fail to embrace the AI chatbots and, as a result, will not be able to use them effectively, fostering resistance and underutilization of the technology. The issue of closing this skills gap imposes an extra layer of complexity on the adoption process (Raut et al., 2018; Singh & Rathi, 2021; Tubadji et al., 2021).

2.2.9. Accuracy and reliability

In such areas as accounting and finance, the accuracy and reliability can be a factor in making a difference between financial or legal implications (Almaqtari, 2024; Kar et al., 2021; Kelly et al., 2023). Most professionals are skeptical about using AI software to deliver precise complex tasks (Eziefule et al., 2022). Accuracy in data processing and financial reporting leads to compliance issues or financial losses because of minor inaccuracies. Therefore, without strong evidence that chatbots are correct and accurate most of the time, organizations are not likely to incorporate them in vital workflows but will instead continue to have humans monitor transactions for errors that might lead to costly mistakes (Al-Okaily, 2024).

2.2.10. User trust

User trust would be the key to success of AI chatbot adoption since professionals have to be able to trust that these systems provide accurate, secure, and beneficial outputs (Ahyar Yuniawan et al., 2025; Raut et al., 2018; Singh & Rathi, 2021). However, studies reveal that most users still distrust AI systems because they fear the decision-making ability of those systems and are unclear about their transparency. According to Bansal et al. (2024), one of the major barriers for users is trust in that a user may wonder whether a chatbot can execute sensitive financial operations or deliver the same level of insight as human professionals. Distrust can be traced from the lack of transparency in how AI systems arrive at certain conclusions or decisions, causing a hindrance among users from relying completely on them (Liu et al., 2024; Yenugula et al., 2023).

2.2.11. Customization requirements

Not every organization shares similar functionalities, and generally, one-size-fits-all chatbot solutions cannot suffice. In the industries of accounting and finance, the type of process and workflow is certainly more different between organizations (Jackson & Allen, 2024; Raut et al., 2018; Singh & Rathi, 2021). Thus, off-the-shelf chatbot solutions might not be appropriate to fill the nuanced demands, which makes most organizations need costly customization efforts. As Korhonen et al. (2021) pointed out, it takes a lot of time, and resources to tailor AI chatbots in a way that enables them to fit perfectly into the existing systems and workflows of an organization, and this can also act as a huge barrier to adoption.

2.2.12. Vendor dependence

Most organizations would be hesitant to get locked in for the development, deployment, and maintenance of AI chatbot systems to third-party vendors. Basically, vendor dependence leads to dangerous situations, since sensitive updates, security patches, and all support life cycles would be at the mercy of the third parties (Kar et al., 2021). Sreseli (2023) have indicated that this also restrains the control the organization possesses over the functionality of the chatbot besides future scalability. Further, any failure or inefficiency on the part of the vendor may also have a fallout for the organization in terms of operations resulting from service disruptions and increasing costs (Zhao et al., 2024; Vărzaru, 2022b).

3. Theoretical framework

The study of AI chatbot adoption barriers is rooted in several well-established theoretical models, including the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). Technology Acceptance Model (TAM): TAM is an extensively applied framework which explains the acceptance of technology, where it postulates that perceived usefulness and ease of use are the two factors influencing an individual's decision to adopt new technology (Davis et al., 1989). Applied to AI chatbots, perceived usefulness could be referred to the potential benefits in the task automation and efficiency in accounting and perceived ease of use refers to how intuitive and user-friendly these chatbot systems are for professionals (Alkadi & Abed, 2025; Tiwari et al., 2024; Jierasup & Leelasantitham, 2024). Unified Theory of Acceptance and Use of Technology (UTAUT). The UTAUT extended TAM with four other factors in the model such as social influence and facilitating conditions. Here, social influence is defined as the extent to which people believe others expect them to use the new system, whereas facilitating conditions are "infrastructure and resources that are required in order for an individual to use the technology" (Venkatesh et al., 2003). For AI chatbots this could be social influences when industries are invoking the use of AI whilst enabling conditions are the ability of the requisite infrastructures and supports by the right people to be there for that process to work smoothly (Bhat et al., 2024; Ju et al., 2025; Mohd Rahim et al., 2022). Psychological roots of barriers such as distrust of AI, resistance to change, and fear of job loss are designed in accordance with well- known behavioral theories. The

Technology Readiness Index (TRI) of Parasuraman (2000) can be used for explaining how emotional inhibitors – such as discomfort and insecurity – impact attitude towards automation and chatbot technologies. Furthermore, Organizational Change Theory (Armenakis & Bedeian, 1999) details how internal resistances result from ineffective communication strategies, limited leadership support, and minimal participation. This framework is critical in interpreting the behavioral and institutional inertia evident in chatbot resistance.

In parallel, Arora et al. (2024) used ISM to model adoption barriers in the energy-efficient appliance sector. Their results showed that awareness, trust, and perceived effort were core factors influencing behavioral intent—constructs that directly parallel our chatbot resistance variables. By drawing on these behavioral models, this study deepens its psychological framing of human-centric obstacles, which are both structurally positioned in ISM and quantitatively validated in SEM.

3.1. Diffusion of innovation theory

It can provide useful insights, especially on the understanding of how AI chatbots are diffused within industries (Rogers, 1995). These factors' influence on adoption is said to include relative advantage, compatibility with existing systems, complexity, trialability, and observability. In the case of AI chatbots, instances of perceived complexity and high setup costs and the requirement that these are compatible with legacy systems could hinder the process of diffusion in the accounting industry. These models would now serve as a basis to understand how such differentiated barriers influence the adoption of AI chatbots in professional settings (Gutiérrez-Leefmans et al., 2025; Jierasup & Leelasantitham, 2024). This study, therefore, brings these theoretical frameworks into an effort to explain how human, organizational, and technological factors interplay to either facilitate or impede successful implementation of AI-based solutions. In addition, the ISM and SEM techniques have been applied to analyze the relationships quantitatively and qualitatively between such barriers and identify the most challenging issues in adoption (Mondal et al., 2025; Khuc et al., 2024; Singh & Rathi, 2021).

4. Methodology

This study employs two-step methodology, Interpretive Structural Modeling (ISM) and Structural Equation Modeling (SEM), for examining the adoption barriers of AI chatbots in accounting (Singh & Rathi, 2021; Khaba & Bhar, 2018). In other words, the justification of this methodological triangulation is to permit a comprehensive examination of barriers in a manner that is comprehensive enough to allow for their structural hierarchy as well as to determine their effect. First, the ISM method is employed to examine and classify the factors influencing the adoption of AI Chatbots in the accounting field. This technique offers the possibility to let the problem of inconsistency between the barriers to be addressed, aligning them thus in a diagrammatic ordered ranks to explain the relationships between them (Chavali et al., 2024; Ansari et al., 2024; Kumar et al., 2021). In cases in which ISM is applied, complex issues can be simplified, and known primitive elements can therefore be defined more easily, while qualitative feedback collected from industry workshops validates the model (Katiyar et al., 2024; Ahmad & Qahmash, 2021). The ISM removes the driving and dependent barriers and thereby it is helpful to identifies the most critical factors to be focus for decision makers during the implementation issues (Qureshi et al., 2025; Raut et al., 2018). To theoretically rationalize ISM as the chosen technique, this research is based on well-known established criteria which support the robustness of ISM in revealing hierarchical interrelationships among complex variables (Chuaphun & Samanchuen, 2024; Javan Jafari Bojnordi et al., 2025; Kumar & Goel, 2022). Notably the research by Kumar and Goel (2022) performs a thorough empirical and bibliometric validation of the flexibility and adaptability of the ISM in many domains, such as sustainability, technology management, and strategic planning. This study positions ISM as a valid approach for the study of latent constructs and for the structuring of complex problem spaces. Consequently, the benchmarking of ISM in this study against Kumar and Goel's findings reinforces its methodological soundness in analyzing AI chatbot adoption barriers.

Post-ISM analysis, SEM is employed in this section to quantitatively investigate the interdependent barriers and its effectiveness on the adoption of AI chatbot in accounting profession. Causal interpretation can be joined with that of other variables on the basis of this statistical method (Behl et al., 2023; Bhat et al., 2024). The SEM is an obvious instrument to verify the relationships elicited at the ISM stage, as it facilitates the testing of hypotheses and the assessment of model fit. Moreover, it allows one to examine complex associations to be examined at once and to understand how these interacting but potentially opposite effects act together (Tiwari et al., 2024). The policy makers and industrialists must employ the findings of SEM in developing mechanisms to reduce the impediments that hinder the acceptance of AI applications. This now leads the present analysis to aim to "combine" ISM and SEM in providing a complete picture of what hinders the usefulness of AI-based chatbot systems in accounting.

4.1. Interpretative Structure Modeling (ISM)

Using Warfield's original contribution of ISM, that initially debuted in 1974, the present study investigates the application of Interpretive Structural Modeling (ISM) in identifying the adoption barriers of AI based chatbots among working professionals. ISM suggests a solid framework for carrying out a precise and logical thinking process and implementation (Jadhav et al., 2014; Chen et al., 2022; Mondal et al., 2025). By offering a well-defined approach that is used to this structural synthesis process, ISM enables the integration of the discrete components of a problem into a single model.

Creation and sharing of visualizations that exhibit the complex nature of interactions and relationships among certain issues or concerns in each system is one of the objectives of ISM (Kumar & Goel, 2022; Ahmad and Qahmash, 2021). The usage builds this up through a combination of discrete mathematics modeling languages, digraphs, and acrophobic (vote, or words) elements. These integration tools are either exhibited in words or are combined in digraphs and serve to represent the various components of the problem and the relationships among them. But even beyond just organizing and interpreting the mastered facts and figures it has more analytical techniques. A qualitative rather than a quantitative approach is applied as a way of comprehending the system more holistically as achieving this through a quantitative method may make one miss some of the issues and nuances. Further, studies conducted by Santos et al. (2024) and Yadav et al. (2020) demonstrate that there are specific benefits of this method as compared to that of other modeling methodologies. The need for more experts in employed methods such as the Delphi method or Structural Equation Modeling (SEM) when determining the effectiveness of ISM is not the same as what obtains in application of the ISM. For its low cost and usability, this method is the most used by organizations dealing with complicated problems.

4.2. Analysis

Under ISM, the method of matrix analysis is applied to construct the critical problems, define their relationships, and build the model. First, relevant issues are determined by a questionnaire or an interview. Then relations between two topics are established based on agreement of the experts. Finally, the depictions are made through a structural matrix which brings clarity to the interrelations of the system in focus (Jaziri et al., 2024; Sun et al., 2020). When one follows these steps, it is possible to create a framework that is complete with understanding and tackling the problem at hand.

4.3. Determination of adoption barriers of Chatbots among working professionals

In the first instance, we studied the accounting and finance professionals' attitude towards the use of chatbots. For this, we scanned a variety of literature containing the use of chatbots. Several barriers were brought forth in these sources. Then we interview experts who purely dealt with technology, accounting, and finance. Out of sixty-six people which we sent a questionnaire to, twenty-nine responded. About this type of survey, this is acceptable because response rate of such high 44 % is acceptable (Chavali et al., 2024). We also had experts rank these barriers on a numerical scale to make further conclusions (Table 1). This scale provides the opportunity to ascertain the degree of sentiment each barrier held among experts. The responses of the experts were highly consistent as Cronbach's α coefficient for the evaluation was at 0.84. This is encouraging since it means that the respondents did not drift much from the majority opinion. Table 2 present the list of barriers identified through review of literature.

4.4. Structured Self- interaction matrix development

The next step in the research was devoted to the construction of an ISM-based Structural Self-Interaction Matrix (SSIM) (Sathyan et al., 2024; R & Vinodh, 2021). At this stage, the study became more interpretative as it sought an explanation of how the different factors were interrelated, by analyzing the responses of the respondents and the available literature. Hence the SSIM was designed and explained in detail in Table 3. To explain the interaction between two barriers, symbols were assigned to them as follows: 'V' – meaning Barrier i affected Barrier j, 'A' – Barrier j affected Barrier i, 'X' – both barriers affected each other – while '0' meant no relationship between the two barriers was observed.

Table 1
Profile of experts.

Experts	Qualifications	Area of expertise
1	PhD in Systems Engineering	Pioneer of ISM methodology
2	PhD in Finance & AI Systems	AI chatbot systems in finance
3	PhD in Computer Science	AI-driven NLP systems
4	PhD in Business Analytics	AI adoption barriers in finance
5	PhD in Economics	Cost analysis for AI implementation
6	PhD in Information Systems	Data privacy in AI systems
7	PhD in Accounting Technology	AI integration in accounting systems
8	PhD in Finance & ISM	Barriers to AI in financial services
9	PhD in Legal Compliance	Regulatory frameworks for AI
10	PhD in Data Science	Trust in AI systems
11	PhD in Management Studies	ISM and decision-making models
12	PhD in AI Systems	Customization of AI chatbots for finance
13	PhD in AI Integration	Skill gaps in AI technology adoption
14	PhD in Information Systems	Legacy system integration with AI
15	PhD in Information Privacy	AI chatbot adoption
16	PhD in Digital Marketing	User experience with AI chatbots
17	PhD in Software Engineering	Development of AI algorithms
18	PhD in Cybersecurity	Security risks in AI implementation
19	PhD in Human-Computer Interaction	User interface design for AI chatbots
20	PhD in Behavioral Economics	Consumer acceptance of AI technologies
21	PhD in Operations Management	Efficiency of AI in business processes
22	PhD in Telecommunications	AI and communication systems
23	PhD in Organizational Psychology	AI impact on workplace dynamics
24	PhD in Data Analytics	Metrics for AI performance evaluation
25	PhD in Mobile Computing	AI applications in mobile technology
26	PhD in Marketing	Marketing strategies using AI chatbots
27	PhD in Supply Chain Management	AI in logistics and supply chain optimization
28	PhD in Robotics	AI integration in robotic systems
29	PhD in Social Science	Societal implications of AI technology

Source: Authors' compilation.

Table 2
List of barriers.

Barriers	References
Lack of understanding and Awareness	(Ahyar Yuniawan et al., 2025; Jackson & Allen, 2024; Kar et al., 2021; Liu et al., 2024; Singh & Rathi, 2021; Yenugula et al., 2023)
High initial cost	(Zaidi et al., 2025; Bansal et al., 2024; Gkinko & Elbanna, 2023; Vărzaru, 2022a; Kar et al., 2021; Tubadji et al., 2021; Raut et al., 2018)
Data privacy concerns	(Ahyar Yuniawan et al., 2025; Brachten et al., 2021; Gkinko & Elbanna, 2023; Kar et al., 2021; Rababah et al., 2022; Zhao et al., 2024)
Regulatory compliance	(Kar et al., 2021; Kelly et al., 2023; Shakdwipee et al., 2023).
Technological infrastructure	(Zaidi et al., 2025; Bansal et al., 2024; Vărzaru, 2022b; Kar et al., 2021; Raut et al., 2018)
Integration with existing systems	(Jackson & Allen, 2024; Almaqtari, 2024; Sreseli, 2023; Tubadji et al., 2021)
Resistance to change	(Ahmed et al., 2025; Chavali et al., 2024; Yenugula et al., 2023; Vărzaru, 2022a; Kar et al., 2021)
Skill gap	(Zaidi et al., 2025; Bansal et al., 2024; Saad et al., 2023; Singh & Rathi, 2021; Tubadji et al., 2021; Raut et al., 2018;)
Accuracy and reliability	(Almaqtari, 2024; Al-Okaily, 2024; Eziefule et al., 2022; Kar et al., 2021; Kelly et al., 2023)
User trust	(Ahyar Yuniawan et al., 2025; Bansal et al., 2024; Liu et al., 2024; Raut et al., 2018; Singh & Rathi, 2021; Yenugula et al., 2023)
Customization requirements	(Jackson & Allen, 2024; Korhonen et al., 2021; Raut et al., 2018; Singh & Rathi, 2021)
Vendor dependence	(Zhao et al., 2024; Sreseli, 2023; Vărzaru, 2022b; Kar et al., 2021)

Source: Authors' compilation.

4.5. Design of Reachability Matrix

Certain techniques adhere to the transformation specified for the matrix in Table 4 as its Structural Similarity Index Matrix is converted to a binary reachability matrix (Pramod et al., 2023; Yadav et al., 2020). Following this, the driving power and the dependence of active means fearing the structural conditions are calculated. All the results are compiled in Table 5 at the end of the sections.:

4.6. Level partitioning

In the ISM method, the reachability matrix is divided into levels according to the driving and dependent variables (Katiyar et al., 2024; Poduval et al., 2015; Roy & Modak, 2023). Analysis of other risk factors and planning dimensions has been made in practice, Table 6 showing the sets of obstacles' accessibility and the states preceding each set of obstacles. The relevancy set is the barrier itself as well as the related barrier or barriers that could assist in removing it, while antecedent contain the barrier as well as other barriers and other elements which will influence the occurrence of the barrier. The intersection set consists of reachability and antecedent sets. Such restrictions to the implementation of AI chatbots among selected working professionals have been divided into level 1 barriers which are the highest in hierarchy in the ISM model then level 2, 3, 4, and 5 as it comes out of the analysis. (See Table 6.)

4.7. Conical matrix development

The reachability matrix is fragmented, and the barriers are gathered into a level. It offers to ascend to a conical matrix within which barriers of identical levels are categorized collectively. (Table 7). Therefore, the major barrier for AI chatbots adoption among working professionals are

Table 3
Structural Self-Interaction Matrix (SSIM).

Variables	1	2	3	4	5	6	7	8	9	10	11	12
Lack of understanding and Awareness		O	O	O	O	O	V	O	O	V	O	O
High Initial Cost			O	O	V	V	V	A	V	V	V	V
Data Privacy Concerns				V	A	A	V	A	V	V	O	V
Regulatory Compliance					A	A	A	A	V	V	O	V
Technological Infrastructure						V	V	A	V	V	V	V
Integration with existing systems							A	A	V	V	V	V
Resistance to change								A	A	A	A	A
Skill Gap									V	V	V	V
Accuracy and Reliability										V	V	V
User Trust											V	V
Customization Requirements												V
Vendor Dependence												

Source: SmartISM Output.

Table 4
Reachability Matrix (RM).

Variables	1	2	3	4	5	6	7	8	9	10	11	12	Driving power
Lack of understanding and awareness	1	0	0	0	0	0	1	0	0	1	0	0	3
High initial cost	0	1	0	0	1	1	1	0	1	1	1	1	8
Data privacy concerns	0	0	1	1	0	0	1	0	1	1	0	1	6
Regulatory compliance	0	0	0	1	0	0	0	0	1	1	0	1	4
Technological infrastructure	0	0	1	1	1	1	1	0	1	1	1	1	9
Integration with existing systems	0	0	1	1	0	1	0	0	1	1	1	1	7
Resistance to change	0	0	0	1	0	1	1	0	0	0	0	0	3
Skill gap	0	1	1	1	1	1	1	1	1	1	1	1	11
Accuracy and Reliability	0	0	0	0	0	0	1	0	1	1	1	1	5
User trust	0	0	0	0	0	0	1	0	0	1	1	1	4
Customization requirements	0	0	0	0	0	0	1	0	0	0	1	1	3
Vendor dependence	0	0	0	0	0	0	1	0	0	0	0	1	2
Dependence power	1	2	4	6	3	5	10	1	7	9	7	10	

Source: SmartISM Output.

Table 5
Final Reachability Matrix (FRM).

Variables	1	2	3	4	5	6	7	8	9	10	11	12	Driving power
Lack of understanding and Awareness	1	0	1*	1*	0	1*	1	0	1*	1	1*	1*	9
High initial cost	0	1	1*	1*	1	1	1	0	1	1	1	1	10
Data privacy concerns	0	0	1	1	0	1*	1	0	1	1	1*	1	8
Regulatory compliance	0	0	1*	1	0	1*	1*	0	1	1	1*	1	8
Technological infrastructure	0	0	1	1	1	1	1	0	1	1	1	1	9
Integration with existing systems	0	0	1	1	0	1	1*	0	1	1	1	1	8
Resistance to change	0	0	1*	1	0	1	1	0	1*	1*	1*	1*	8
Skill gap	0	1	1	1	1	1	1	1	1	1	1	1	11
Accuracy and Reliability	0	0	1*	1*	0	1*	1	0	1	1	1	1	8
User trust	0	0	1*	1*	0	1*	1	0	1*	1	1	1	8
Customization requirements	0	0	1*	1*	0	1*	1	0	1*	1*	1	1	8
Vendor dependence	0	0	1*	1*	0	1*	1	0	1*	1*	1*	1	8
Dependence power	1	2	12	12	3	12	12	1	12	12	12	12	

Source: SmartISM Output.

data privacy concerns, regulatory compliance, integration with existing systems, resistance to change, accuracy and reliability, user trust, customization requirements, vendor dependence are categorized into level 1 followed by Lack of understanding and Awareness, Technological Infrastructure at level 2 whereas High Initial Cost at level 3 and skill gap at level 4 (Table 8). The subsequent conical matrix supports in the coming up with the digraph and structural model. It elaborates the various aspects of the antecedent, reachability and intersection sets for each barrier to grasp the relationships and levels.

4.8. ISM Model

In the subsequent phase, a tentative digraph is created by using the conical matrix and incorporating transitivity relationships. The digraph is represented by nodes and lines, with transitivity links portrayed as dotted lines and direct relationships depicted as straight lines (See Fig. 1). The study identified that the variables referred to as 'data privacy concerns', 'regulatory compliance', 'integration with existing systems', 'resistance to change', 'accuracy and reliability', 'user trust', 'customization requirements', and 'vendor dependence' are the most prominent obstacle at the topmost level of the hierarchy. Additionally, this study has highlighted other variables such as Lack of understanding and Awareness, Technological Infrastructure, High Initial Cost, and skill gap serves as significant obstacles in chatbots adoption. To tackle these interconnected challenges, it is essential to adopt a comprehensive approach that identifies and leverages the significant benefits and incentives for organizations, governments, and key stakeholders.

This is also a common phenomenon found within the MICMAC Analysis (See Fig. 2). Those barriers that have been revealed, this study classifies them in to the four different categories based on the level of

Table 6
Level Partitioning (LP).

Elements (Mi)	Reachability Set R(Mi)	Antecedent Set A (Ni)	Intersection Set R (Mi)∩A(Ni)	Level
1	1,	1,	1,	2
2	2,	2, 8,	2,	3
3	3, 4, 6, 7, 9, 10, 11, 12,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,	3, 4, 6, 7, 9, 10, 11, 12,	1
4	3, 4, 6, 7, 9, 10, 11, 12,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,	3, 4, 6, 7, 9, 10, 11, 12,	1
5	5,	2, 5, 8,	5,	2
6	3, 4, 6, 7, 9, 10, 11, 12,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,	3, 4, 6, 7, 9, 10, 11, 12,	1
7	3, 4, 6, 7, 9, 10, 11, 12,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,	3, 4, 6, 7, 9, 10, 11, 12,	1
8	8,	8,	8,	4
9	3, 4, 6, 7, 9, 10, 11, 12,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,	3, 4, 6, 7, 9, 10, 11, 12,	1
10	3, 4, 6, 7, 9, 10, 11, 12,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,	3, 4, 6, 7, 9, 10, 11, 12,	1
11	3, 4, 6, 7, 9, 10, 11, 12,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,	3, 4, 6, 7, 9, 10, 11, 12,	1
12	3, 4, 6, 7, 9, 10, 11, 12,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,	3, 4, 6, 7, 9, 10, 11, 12,	1

Source: SmartISM Output.

Table 6
Level partitioning iterations.

Elements (Mi)	Reachability Set R (Mi)	Antecedent Set A (Ni)	Intersection Set R(Mi)∩A(Ni)	Level
1	1, 3, 4, 6, 7, 9, 10, 11, 12,	1,	1,	
2	2, 3, 4, 5, 6, 7, 9, 10, 11, 12,	2, 8,	2,	
3	3, 4, 6, 7, 9, 10, 11, 12,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,	3, 4, 6, 7, 9, 10, 11, 12,	1
4	3, 4, 6, 7, 9, 10, 11, 12,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,	3, 4, 6, 7, 9, 10, 11, 12,	1
5	3, 4, 5, 6, 7, 9, 10, 11, 12,	2, 5, 8,	5,	
6	3, 4, 6, 7, 9, 10, 11, 12,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,	3, 4, 6, 7, 9, 10, 11, 12,	1
7	3, 4, 6, 7, 9, 10, 11, 12,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,	3, 4, 6, 7, 9, 10, 11, 12,	1
8	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,	8,	8,	
9	3, 4, 6, 7, 9, 10, 11, 12,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,	3, 4, 6, 7, 9, 10, 11, 12,	1
10	3, 4, 6, 7, 9, 10, 11, 12,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,	3, 4, 6, 7, 9, 10, 11, 12,	1
11	3, 4, 6, 7, 9, 10, 11, 12,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,	3, 4, 6, 7, 9, 10, 11, 12,	1
12	3, 4, 6, 7, 9, 10, 11, 12,	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12,	3, 4, 6, 7, 9, 10, 11, 12,	1

Source: SmartISM Output.

dependence and the impact of the barrier (Chavali et al., 2024; Kumar et al., 2021; Yadav et al., 2020). Cluster I comprise of "autonomous variables" which have low interdependence as well as low driving force. Cluster II is inhabited by what are called "dependent variables" which cannot undertake change initiation on their own to any appreciable degree but are very change responsive and are dependent to a large degree. Cluster III is made up of "linkage variables" that experience high levels of driving forces and dependence, and thus are very critical in shaping the overall system dynamics of the system. Cluster IV consists of "autonomous variables" which cause changes to be effects but do not follow the change.

4.9. PLS-SEM methodology

During the second phase, the study utilized SEM data analysis techniques to investigate the linear correlations among the variables derived from the conceptual model established by ISM analysis (Rigdon, 1998; Shah & Goldstein, 2006). The ISM model was rigorously analyzed using PLS-SEM techniques. During this phase of data analysis, the researchers performed a confirmatory factor analysis to evaluate the measurement model, then assessing the structural model (Hair et al., 2017). SmartPLS 4.0 was employed to statistically evaluate the relationships between variables.

Partial least squares structural equation modeling (PLS-SEM) is a technique that resolves estimated relationships among observed and latent constructs across a sophisticated structure. When there are numerous expected results, and the sampling for them is small, this approach is especially helpful. PLS-SEM has been used in various management research as well as in studies in marketing and sociology. It serves to test the ratio of a certain measure of variation or heterogeneity to the measure of estimate according to the introduced relations. It builds up a latent construct and then goes on to model the relationships among both unobserved and observed constructs. PLS–SEM is capable of running both measurement and structural models in one go and is therefore very efficient in testing hypotheses. A possible advantage of PLS-SEM is the ability to analyze non-normality small sample sizes; a crucial solution to most of the social sciences' problems. Moreover, the AMOS method can handle reflective and formative indicators, which makes it have more advantages to use structural equation modeling (SEM) measurement models over other SEM procedures. In addition, scholars are encouraged to draw on the best practice and guidance suggested by Hair et al. (2019) and Ringle et al. (2012) can be utilized for performing reliable PLS-SEM research.

These guidelines state that construct validity must be established, model fit must be assessed, and there should be a detailed and honest reporting of the results. The PLS–SEM approach comprises three differentiation levels (in serial order); Initially, one specifies a conceptual model that is formed with sound theory and literature (including latent constructs and hypotheses). Then, data is collected based on the model objectives and the established measurement scales. Prior to analyzing it, the data undergoes quality assurance controls, and is filtered to remove any incompatible content. Path and loading values are calculated sequentially for the model, using specific software. Various fit indices are also employed to evaluate the goodness of fit of the model to the data. The results are then interpreted in proper order with their corresponding implications for the hypotheses and theory. The stages are designed to offer a general guideline for conducting research (Hair et al., 2017).

Moreover, this research uses a two-stage approach for verification, including both the EFA and CFA, to validate the construct measurement of `barrier'. EFA was performed to explore underlying structures among the items, and CFA was employed to establish construct validity and to test the model fit with existing theoretical assumptions.

This dual approach is empirically supported in the methodological literature and out-of-domain predecessors provide additional support for its validity. Khan et al. (2025) demonstrated the integration of hybrid models and domain knowledge to validate predictive frameworks in healthcare. This approach echoes the value of combining data-driven exploration with theoretical validation, thereby supporting our methodological decision to apply both EFA and CFA in a complementary manner. Such integration is particularly relevant in multidisciplinary studies where constructs are complex, and validation demands both statistical rigor and conceptual alignment.

4.10. Research context (SEM)

When we look at developing countries like India, the services sector especially the aspects of accounting, finance and taxation is extremely important since it is the one that drives economic development. Although such sectors are rudimentary to business activities, compliance and general economy growth, their integration with modern automated

Table 7
Conical Matrix (CM).

Variables	3	4	6	7	9	10	11	12	1	5	2	8	Driving power	Level
3	1	1	1*	1	1	1	1*	1	0	0	0	0	8	1
4	1*	1	1*	1*	1	1	1*	1	0	0	0	0	8	1
6	1	1	1	1*	1	1	1	1	0	0	0	0	8	1
7	1*	1	1	1	1*	1*	1*	1*	0	0	0	0	8	1
9	1*	1*	1*	1	1	1	1	1	0	0	0	0	8	1
10	1*	1*	1*	1	1*	1	1	1	0	0	0	0	8	1
11	1*	1*	1*	1	1*	1*	1	1	0	0	0	0	8	1
12	1*	1*	1*	1	1*	1*	1*	1	0	0	0	0	8	1
1	1*	1*	1*	1	1*	1	1*	1*	1	0	0	0	9	2
5	1	1	1	1	1	1	1	1	0	1	0	0	9	2
2	1*	1*	1	1	1	1	1	1	0	1	1	0	10	3
8	1	1	1	1	1	1	1	1	0	1	1	1	11	4
Dependence power	12	12	12	12	12	12	12	12	1	3	2	1		
Level	1	1	1	1	1	1	1	1	2	2	3	4		

Source: SmartISM Output.

Table 8
Reduced Conical Matrix (CM).

Variables	3	4	6	7	9	10	11	12	1	5	2	8	Driving power	Level
Data privacy concerns	1	1	1*	1	1	1	1*	1	0	0	0	0	8	1
Regulatory compliance	1*	1	1*	1*	1	1	1*	1	0	0	0	0	8	1
Integration with existing systems	1	1	1	1*	1	1	1	1	0	0	0	0	8	1
Resistance to change	1*	1	1	1	1*	1*	1*	1*	0	0	0	0	8	1
Accuracy and Reliability	1*	1*	1*	1	1	1	1	1	0	0	0	0	8	1
User trust	1*	1*	1*	1	1*	1	1	1	0	0	0	0	8	1
Customization requirements	1*	1*	1*	1	1*	1*	1	1	0	0	0	0	8	1
Vendor dependence	1*	1*	1*	1	1*	1*	1*	1	0	0	0	0	8	1
Lack of understanding and Awareness	1*	1*	1*	1	1*	1	1*	1*	1	0	0	0	9	2
Technological infrastructure	1	1	1	1	1	1	1	1	0	1	0	0	9	2
High initial cost	0	0	0	0	0	0	0	0	0	1	1	0	10	3
Skill gap	0	0	0	0	0	0	0	0	0	0	1	1	11	4
Dependence power	12	12	12	12	12	12	12	12	1	3	2	1		
Level	1	1	1	1	1	1	1	1	2	2	3	4		

Source: SmartISM Output.

solutions such as AI powered chatbots proves to be a challenge. Natural language processing and machine language based technological solutions such as AI chatbot tools have a potential to change and revolutionize the works of professionals in accounting, finance, and taxation (Alabed et al., 2022). They can make processes more efficient, facilitate better the decision-making processes, and enhance service delivery (Betz et al., 2023; Gupta et al., 2021). For instance, AI powered chatbots provide automated solutions to menial jobs, recommend financial solutions in a timely manner, help in tax fillings and general compliance with the rules and regulations of the land (Ruiz, 2021) Such a technological progress increases productivity and cuts down operational costs considerably. But there are obstacles to using these tools in an effective manner especially in developing economies like India. Artificial intelligence can assist in addressing numerous basic tasks directed to AI-powered virtual assistants leaving no questions unattended by making the adoption of new and innovative solutions.

4.11. Data collection (SEM)

The present study collected useful insights from practicing accountants in India. From June to September 2024, quantitative data was obtained through self-administered questionnaires directed to accountants, financial managers, and auditors. Surveys were sent out to 390 potential respondents through which robust response rate of 76.41 % was achieved where 298 completed questionnaires were returned. To ascertain the suggested theoretical model, the study devised a measurement instrument which synthesized appropriate scales from existing literature. Likert scale which is a robust agreement scale used was employed to measure all constructs which ranged from level 1 (strongly disagree) to level 5 (strongly agree). Prior to widespread distribution, the researchers had two accountants, two financial managers, and two auditors examine the proposed scales to validate content validity. Their expert feedback led to adjustments in question wording and modifications to better cater the instrument towards the target sample. This preemptive review proved prudent, as it allowed refinement of the survey to capture more nuanced and meaningful insights for analysis.

4.12. Method bias test (SEM)

Common method bias was used by adopting a series of diagnostic approaches to validate the integrity of our data. Particularly, we perform the Harman single-factor test on the entire set of collected data. In that respect, considering that our proposed model includes ten constructs, following previous research advice, the data analysis revealed that the highest variance explained by a single latent factor was 25.61 %, which was below the critical threshold of 50 %. Thus, common method bias appears to be an insignificant concern.

To further confirm this finding, we utilize the marker variable technique and introduce a theoretically unrelated marker variable to estimate the shared variance. Here, we consider the null correlation of the marker variable with the substantive constructs, further supporting the trivial presence of common method bias. Furthermore, we implemented the so-called common latent factor approach within our structural model, assuming the existence of an unmeasured latent factor that impacts all observed variables. The results indicated non-significant diverse in standardized regression weights from the model without the common latent factor, which also confirms the previous findings. Additionally, we identified natural differences in response distributions observed among respondents that varied between more detailed reflections in long items and brief explanations in short items. Therefore,

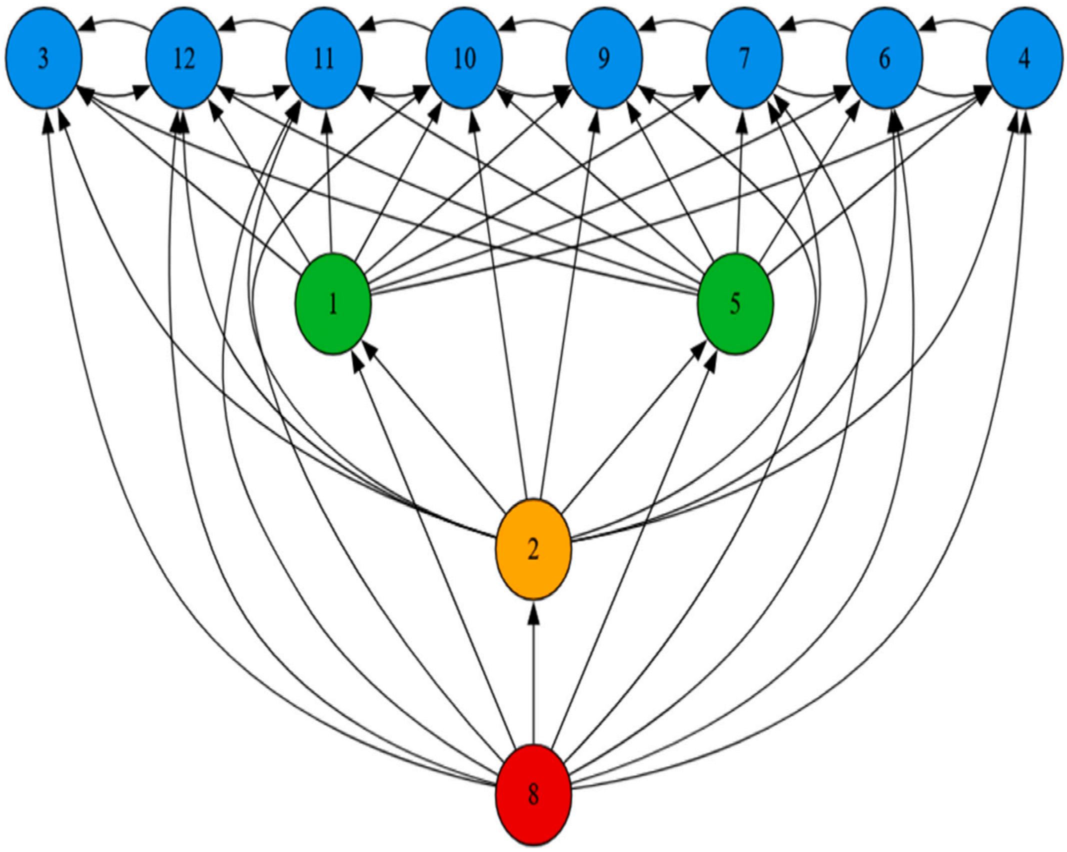

Fig. 1. ISM Model.
Source: Author's Compilation from Graphviz.

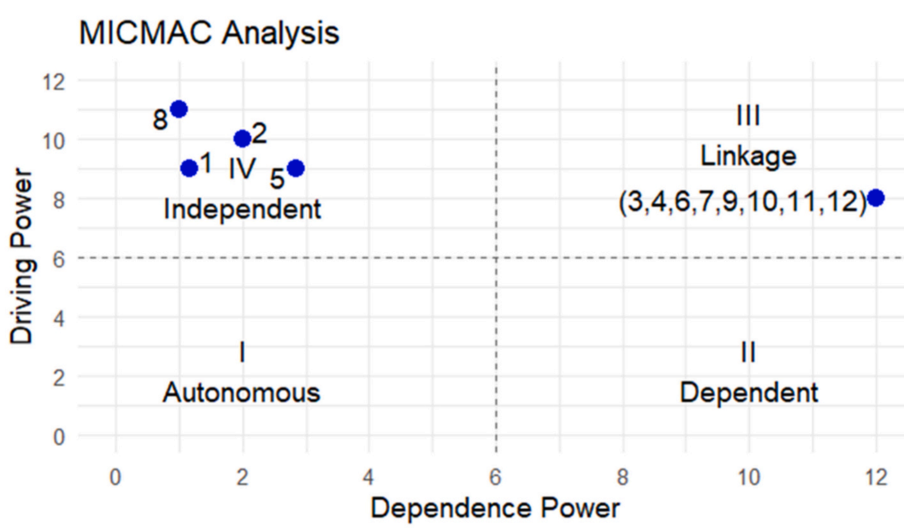

Fig. 2. MICMAC analysis.
Source: Author's Compilation from RStudio.

our triangulation of the three techniques validated that common method bias poses no such threat to the validity of our conclusions.

4.13. Exploratory factor analysis (EFA)

From the beginning, compiling the data from twelve noted barriers into a fresh document utilizing Exploratory Factor Analysis (PCA with varimax rotation) through SPSS (version 24) was employed to examine construct validity (Patyal & Koilakuntla, 2015) and utilize a smaller grouping of unrelated variables (Ngai & Cheng, 1997). Furthermore, the outcomes of the factor examination were validated utilizing the steps of sample suitability evolved by Kelvin-Meyer-Olkin (KMO) and the Bartlett test of sphericity (Field, 2013). Table 9 illustrates the discoveries of the factor investigation with extracted elements, as well as relating factor scores, eigenvalues, and variance, in addition to the KMO measure, Bartlett's test, and reliability results for every element. Four

Table 9
Exploratory factor analysis results.

Items	CVB	HOB	TDB	TIB
CVB1	0.731	0.408	0.425	0.396
CVB2	0.834	0.524	0.419	0.234
CVB3	0.841	0.587	0.445	0.237
HOB1	0.556	0.859	0.517	0.284
HOB2	0.563	0.882	0.529	0.263
HOB3	0.516	0.834	0.607	0.248
TDB1	0.397	0.483	0.843	0.306
TDB2	0.439	0.559	0.882	0.321
TDB3	0.522	0.592	0.833	0.253
TIB	0.261	0.237	0.296	0.827
TIB1	0.334	0.292	0.298	0.834
TIB2	0.291	0.241	0.264	0.852
Initial Eigen value	3.78	2.89	2.70	1.80
Cumulative percentage of variance extracted	23.08	42.60	59.96	73.54

Source: SPSS output.

components – Technological and Integration obstacle, Human and Organizational hindrance, Cost and Vendor-Related impediment, Trust, and Data issues barriers– were retrieved in view of comparable variance-covariance highlights. As indicated by Field (2013), every one of the factor loadings in Table 9 are inside the admissible scope. More than 60 % of the aggregate rate clarified by the elements was found, which is fundamentally more prominent than the most reduced figure of 50 % expressed by (Hair et al., 2019). Moreover, it was found that the KMO estimate's an incentive was higher than the lowest required esteem of 0.5. The Bartlett's test outcome demonstrated that there is a huge connection between the factors (i.e., $p < 0.001$). All recovered parts had Cronbach's alpha higher than the suggested threshold of 0.6. The previously mentioned results approve the review instrument's construct validity.

4.13.1. Development of hypotheses Model and related hypotheses are illustrated in Fig. 4. The hypotheses below have been tested for the model validation

H1. Technological and Integration barrier have a positive impact on Human and Organizational barrier.

H2. Technological and Integration barrier have a positive impact on Cost and Vendor-Related barrier.

H3. Technological and Integration barrier have a positive impact on Trust and Data Concerns barrier.

H4. Human and Organizational barriers have a positive impact on the Trust and Data Concerns barrier.

H5. Cost and Vendor-Related barrier have a positive impact on Trust and Data Concerns barrier.

H6. Human and Organizational barrier have a positive impact on Cost and Vendor-Related barrier.

Notably, the quantitative study incorporated principal component analysis with orthogonal transformation to derive constructs with eigenvalues exceeding unity. Collectively, the extracted factors elucidated 73.54 % of the total variation. The Kaiser-Meyer-Olkin measure evaluated the sampling adequacy as strong at 0.819, signifying robust correlation between variables. Bartlett's test of sphericity generated a chi-square statistic of 1013.22 with 67 degrees of freedom and was significant at the 0.05 level, validating the suitability of factor analysis. Reliability was deemed acceptable across constructs, with Cronbach's alpha coefficients ranging from 0.72 to 0.82. Specifically, principal component analysis with varimax rotation was implemented to categorize the 12 identified barriers into 4 groupings predicated on the extracted factors. The Kaiser-Meyer-Olkin measure of 0.811 reflected an adequate sample size to justify factor analysis. As exhibited in Table 9, all items satisfied the minimum requirement, thereby substantiating the measurement model's dependability and implying sufficiency of the data set for further inspection.

4.14. Analysis of measurement models

Tables 11 and 12 display the findings from the measurement model. First, Cronbach's alpha, composite reliability, and rho A were calculated to determine the reliability of the data. These measures ranged from 0.72 to 0.82, falling within the recommended scope of 0.6–0.9, demonstrating satisfactory consistency. Confirmatory factor analysis was then applied to generate indicator loadings. The results validated those of the exploratory factor analysis. As shown in Table 10, and Fig. 3 shows that all indicator loadings exceeded 0.5, and each average variance extracted value far surpassed the proposed threshold of 0.5, signifying sufficient convergent validity. Discriminant validity of the constructs was assessed using observed data. The guidelines from prior research were employed to evaluate if the constructs exhibited discriminant validity. This process mandates that for any pair of constructs in the measurement model, the correlation coefficient must be lower than the square root of the average variance extracted. In Table 11, the diagonal components representing the square root of average variance extracted exceeded the corresponding row correlation coefficients. This substantiates the presence of discriminant validity. The model fit was deemed acceptable based on the SRMR of 0.062 and NFI of 0.913, as suggested previously.

4.15. Evaluating the structural model

Following verification of the measurement model's suitability, a structural model evaluation was conducted. The variance inflation factor values for all obstacles were assessed to detect any issues with collinearity. It was apparent that the VIF values fluctuated between 1 and 3, signifying that collinearity was not an issue. The coefficient of determination values for the endogenous constructs was evaluated to assess the model's explanatory abilities Fig. 4. The calculated R^2 values for CVB, HOB, and TDB were 0.431, 0.095, and 0.455 respectively. These results demonstrate that the model has predictive importance. The predictive validity of the proposed model was cross-checked using a blindfolding process. The outcomes revealed that the model had good quality and fit as all variables had positive values for the cross-validated redundancy and communality measures.

The significance of the path model was finally evaluated by bootstrapping with 3000 samples, recommended by prior literature (Bhat et al., 2024). Results of this study are reported in Table 12 and Fig. 4. The relationships between the barriers (Technological and Integration Barrier, Human and Organizational Barrier, Cost and Vendor Related Barrier, Trust and Data Concerns Barrier) and their influences on one another are shown in Table 12. The strength and signifi cance of these relationships are indicated by the path model coefficients and statistical significance values. H1 is supported for which TIB has a moderate positive effect on HOB with path coefficient of 0.309 and significant at high level. This implies that the technical and the integration challenges are adding substantially to the human and organizational barriers.

H2 shows that there is a positive, but less strong, effect of TIB on

Table 10
Confirmatory factor analysis.

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
CVB	0.722	0.729	0.844	0.645
HOB	0.821	0.821	0.894	0.737
TDB	0.813	0.817	0.889	0.727
TIB	0.788	0.792	0.876	0.702

Source: SmartPLS output.

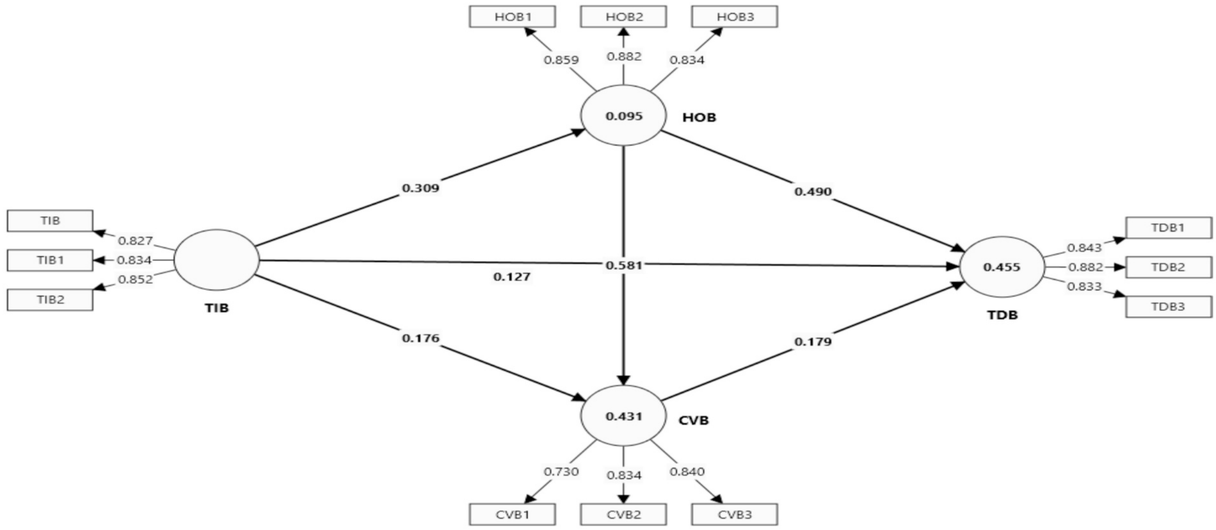

Fig. 3. Measurement model.
Source: SmartPLS output.

Table 11
Discriminant validity.

	CVB	HOB	TDB	TIB
HTMT				
CVB				
HOB	0.82			
TDB	0.694	0.781		
TIB	0.475	0.381	0.428	
F/L				
CVB	0.803			
HOB	0.635	0.858		
TDB	0.535	0.643	0.853	
TIB	0.355	0.309	0.342	0.838

Source: SmartPLS output.

CVB, that is, technology related problems also influence the purchase cost and providers acquisitions barriers. Similarly, H3 indicates a smaller but still significant influence of TIB on TDB, implying that the technological hurdles also influence trust and data issues albeit to a lower extent. H4 The HOB has a positive effect on TDB HOB has a strong effect on TDB, indicating that human and organizational issues substantially contribute to both trust and data concerns. Further, H5, indicates that CVB have positive influence on TDB, reflecting cost barriers and vendor-related barriers also mediate trust and data barrier.

Lastly, H6 provides evidence of a strong positive correlation between HOB and CVB, meaning that organizational barriers exert a direct strong impact on cost and vendor issues. In summary, our study illustrates that these barriers are interconnected, with technological and integration challenges having an indirect influence on trust and data concerns through human, organizational, cost, and vendor factors. Addressing these barriers holistically is crucial for mitigating their combined effects on organizational operations and data management.

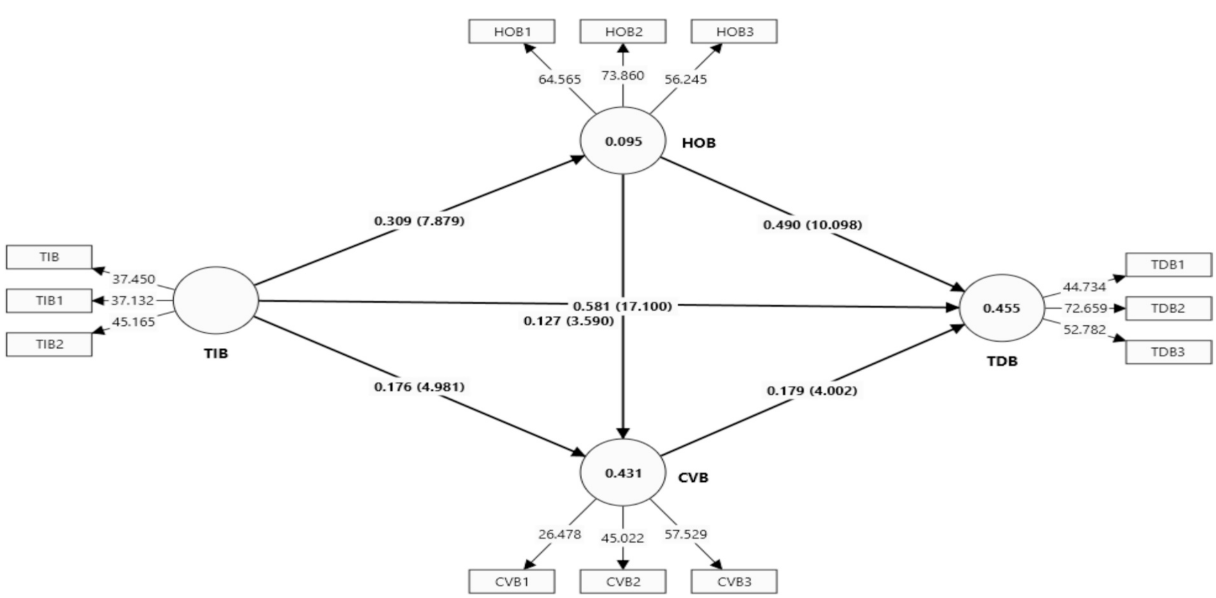

Fig. 4. Structural model.
Source: SmartPLS output.

Table 12
Results for path relationship.

Hypothesis	Path model	Path coefficient (β)	Standard deviation	T statistics	*P* values	2.50 %	97.50 %
H1	TIB→HOB	0.309	0.039	7.879	0.000	0.229	0.384
H2	TIB→CVB	0.176	0.035	4.981	0.000	0.107	0.244
H3	TIB→TDB	0.127	0.035	3.590	0.000	0.058	0.196
H4	HOB→TDB	0.490	0.049	10.098	0.000	0.39	0.582
H5	CVB→TDB	0.179	0.045	4.002	0.000	0.092	0.267
H6	HOB→CVB	0.581	0.034	17.100	0.000	0.514	0.646

Source: SmartPLS output.

5. Results and discussion

Considering the trends and characteristics of AI adoption in the professional environment, and above all, in accounting and finance, there are serious human-oriented aspects that constitute an impediment. We identified critical barriers using an analytically based multi-method approach incorporating both ISM and SEM techniques (Liu et al., 2025; Khaba et al., 2021). Leading are such barriers as “data privacy issues”, “compliance with legal requirements”, “adapting tools to working processes”, “trust in the processes”, “adopting new technologies”, “outlook for performance effectiveness”. This is the highest level in the ISM hierarchy, and it means that these will have a great effect on the adopters (Xu & Zou, 2020). Through this type of investigation, not only barriers, but also the relation between the barriers is analyzed. It indicates the need for an organization to be complex even when contemplating the use of the chatbot technology in the business processes.

ISM methodology makes it easy to analyze the relationship of these barriers to the adoption. With the help of ISM, the adoption of AI chatbots among working professionals is significantly influenced by a range of barriers, which can be systematically categorized into levels based on their impact and complexity (Ju et al., 2025; Pillai et al., 2024). At Level 1 the challenges are many, including data privacy, compliance with regulations, system incompatibility and integration with the existing ones, reluctance from users, trust in accuracy and reliability, demand for most of these from users, and vendor dependence (Nicoletti & Appolloni, 2025; Chellasamy et al., 2025; Bhat et al., 2024; Horani et al., 2023). These challenges are important since they undermine the level of acceptance of an organization to use chatbot solutions. For example, in present scenario when organizations govern themselves under strict policies like General Data Protection Regulation (GDPR), issues of privacy related information and compliance to laws are very serious ones (Jørgensen & Ma, 2025; Sarabdeen & Mohamed Ishak, 2025). Moreover, integration of such technology as chatbots into operational processes is highly sought as the absence of such integrations would cause organizations to flourish. Other issues such as the reluctance to accept new technologies as well as the desire to adopt new technologies that can meet the firm’s requirements make this simple. Employees may be resistant to the changes brought about by technology, and organizations may find that standard solutions do not meet their needs. Following Level 1, Level 2 barriers—such as a lack of understanding and awareness about AI chatbots and the limitations of existing technological infrastructure—are significant but less immediate (Godinho Filho et al., 2025; Kar et al., 2021; Raut et al., 2018). There exists lack of understanding among organizations about the usage of chatbot technology and the lack of such knowledge leads to a general avoidance in adopting it (Chellasamy et al., 2025; Singh & Rathi, 2021; Yuan et al., 2025). Also, there could be a resistance of existing systems to support plenty of facilities and resources, which are expected to attract more funding (Bansal et al., 2024; Gkinko & Elbanna, 2023). Usage of ISM as a tool for structural analysis has been justified within the context of digital transformation literature. For example, Goel et al. (2022, b) examined the obstacles to the adoption of Industry 4.0 among SMEs and discovered that the starting difficulty would come from the resistance which has been firmly formed, such as the lack of the labor skills and the lack of the managers’ confidence. These results align with our model’s treatment of such barriers as critical structural triggers rather than surface-level implementation issues.

In a related application, Alawamleh et al. (2023) found innovation culture and practices of knowledge exchange and management and leadership commitment to play a strategic role in enhancing transformation capabilities in emerging economies. Our model reflects these insights by incorporating constructs such as absence of strategic clarity and lack of inter-departmental alignment within the ISM structure, thereby underscoring the necessity of top-down alignment in fostering technology acceptance.

These studies confirm that the deployment of interpretive structural modeling transcends industry and geography, offering a versatile analytical lens that captures the complex layering of innovation resistance across sectors. The current study extends these findings to the AI chatbot context, demonstrating that such modeling approaches can be effectively used to diagnose and address multi-level adoption challenges.

Furthermore, Level 3 and Level 4 barriers as not critical as others, but these are high end costs and gaps in skills which were highlighted through the results. To overcome these barriers organizations allow drawing the inter relations between these barriers in a conical matrix. If they resolve the Level 1 barriers first, like enhancing the trust of the user on the system and the policies concerning data privacy, this can aid in transferring the organization towards level 2 and the rest levels in a seamless manner. Such a systematic approach would be useful in both recognizing and ranking the problems of institutions and create appropriate conditions for further integration of AI to achieve better efficiency and improve user experience (Alshahrani et al., 2024; Bhaskar & Tiwari, 2025; Dwivedi et al., 2021; Hwang et al., 2025).

The dual-method approach adopted in this study provides insights into the interplay between the structural and behavioral barriers to AI chatbot adoption, using the methods of Interpretive Structural Modeling (ISM) and Structural Equation Modeling (SEM). ISM does not just enable us to develop the contextual hierarchy for a set of barriers but also enables us start building this hierarchy from the foundational enablers: resistance to change, lack of top-down leadership commitment and policy ambiguity. These structural obstacles were supported empirically with SEM validating their impact on behavioral constructs such as user resistance and perceived digital readiness.

This methodological concordance is confirmed by former studies with hybrid models. For instance, Goel et al. (2022, b) adopted an ISM-AHP model for identifying barriers of greening HRM practices in educational institutions and stated that institutional inertia and fragmented policy landscapes are deeply embedded in the lower layers of influence. This hierarchical structure mirrors our findings, in which strategic misalignment and skill-related deficiencies emerge as primary obstacles that shape downstream behavioral responses.

In addition, Alawamleh et al. (2023) further consolidates this interpretive approach by exploring that firm- level innovation in emerging markets is dependent on intangible enablers including leadership vision, interdepartmental cooperation and absorptive capacity—dimensions also depicted as high level leverage drivers in our ISM framework. These cross-contextual consistencies not only support the conceptual integrity of our model, but also enhance its generalizability across different types of organizations.

Institutional resistance to AI chatbot implementation was identified in this study not merely as a technical issue but as a deeply structural and cultural one. Absence of executive advocacy, no policy infrastructure and inflexible administrative processes were identified as low level but high influencing factors on the ISM ladder. Such interpretation is consistent with those characterized by Goel et al. (2022, b), which highlighted that even in settings where the technological case for change is clear, sustainable institutional change often faces resistance from established routines and nodes of strategic ambiguity.

These resistance patterns were supported through our MICMAC results, which identified some of these variables as independent drivers with high driving power and low dependency. The theoretical insight here is that unless these foundational barriers are explicitly addressed, downstream efforts such as user training or interface improvement will likely yield limited effectiveness.

The utilization of SEM in the present study played a significant role to confirm the intricate structural relationships among the identified barriers that had supported the findings from ISM (Bhat et al., 2024; Brachten et al., 2021; Kumar et al., 2022). VIF tests were conducted to detect the severity of multicollinearity among the predictors of the barriers. In this instance, data interpretation showed that these numbers for this construct fell well within the 1–3 range (no strong multicollinearity) of the constructs. The importance of this result cannot be overemphasized, as multicollinearity could distort the true associations between variables which could lead to unreliable conclusions. The results are a compelling case to examine the inter-relationships of barriers insofar as multicollinearity effects do not occur. The adjusted determination coefficient (R^2) figures for the constructs occupied by the 'cost and vendor-related barriers', 'human and organizational barriers', and 'trust and data concerns barriers' were set at 0.431, 0.095 and 0.455 respectively. These R^2 values further suggest that the model satisfactorily explains how such barriers interact or act together in regards the acceptance of chatbot technology. Notably, the higher R^2 value for CVB suggests that cost-related issues play a significant role in shaping perceptions and decisions surrounding chatbot adoption, making it imperative for organizations to consider financial implications in their strategic planning (Tan et al., 2025; Gaur et al., 2025; Tubadji et al., 2021; Raut et al., 2018).

Moreover, from the analysis of the structural model, several plentiful correlations were significant specifically the positive correlation of the "Technological and Integration Barriers" (TIB) to the "Human and Organizational Barriers" (HOB) with a path coefficient of 0.309 which shows a moderate positive relationship. This confirms that technological problems are likely to worsen the resistance generated by organizational issues and therefore, some technical issues need to be resolved first to ensure that the transition to adoption of chatbots is as seamless as possible (Gupta et al., 2025; Bansal et al., 2024; Vărzaru, 2022a). Furthermore, the effect of HOB on TDB is also quite interesting; increasing reduction of organizational impediments significantly increases the users' trust and concerns about the data (Gkinko & Elbanna, 2023; Yadav & Ansari, 2025; Zhao et al., 2024). This brings out an important avenue in which organizations can improve users' acceptance of chatbots by creating an atmosphere that enhances the willingness of users to embrace the new technology and its employees. However, the study also showed that cost factors contribute to the complexity of the relationship between trust and organizational barriers as they tend to highlight the need for interaction between financial issues and trust issues of users (Bansal et al., 2024; Gupta et al., 2025; Raut et al., 2018).

These findings, therefore, depicts the need to address the factors that impede chatbot acceptance in a more comprehensive manner including factors namely technological, organizational, and financial, interact with one another to enhance the likelihood of deploying chatbots in professional environments (Yang et al., 2024; Kaushal & Yadav, 2023). This broad comprehension gives organizations with the right knowledge that can help them in dealing with the challenges of AI implementation, which improves the overall experience of the users and optimizes operations further (Rana et al., 2021).

In the stuffing and introduction of the two techniques above – ISM and SEM – even at the very initial step it is obvious that the separateness of the barriers to user adoption is a conceptually ineffective preposition. The barriers to effective implementation of the process should be seen in the context of how organizations understand the nature of each of the barriers and violating such barriers. Also, these necessitates significant investments in both education and infrastructure to enhance user trust or data privacy. Since the identified barriers are multifaceted in nature, there is need for participation of different stakeholders including organizations, technology developers and regulators. It is anticipated that deploying such strategies will help create conditions which are more favorable for successful reproduction of AI initiatives such as chatbots.

6. Implications

6.1. Theoretical contribution

The present study significantly contributes to the theoretical level by explaining the existing barriers of working professionals towards AI chatbot adoption in two methods Structural Equation Modeling (SEM) and Interpretive Structural Modeling (ISM) (Baabdullah et al., 2022; Brachten et al., 2021; Gkinko & Elbanna, 2023). By systematically categorizing various impediments into a hierarchical framework, the research highlights their interrelated nature and cumulative influence on the adoption process (Liu et al., 2024). The ISM framework places importance on critical barriers including data privacy, compliance issues and trust which signifies the fact that there is a need for nuanced understanding of human oriented aspects in such industries like finance and accounting. Further, the study shows that interactions between barriers can enhance or reduce the impact of the barriers, purposefully challenging the idea that these barriers are just an accumulation of factors (Li et al., 2023). This relational view coincides with the theoretical expectation for a holistic integration of technology and the organization in order to achieve effective utilization of technology. Moreover, the empirically validation by SEM also confirms the importance of cost related barrier and there are relations between the technology factors, and human factors and they must also need to be addressed simultaneously, and not in isolation. The study also provides a theoretical reference for combining multi-methods to investigate barriers of technology adoption. The combined implementation of SEM and ISM provides a richer understanding—where ISM suggests a hierarchical relationship, SEM statistically validates these links. Future research could build-out by including Multi-Criteria Decision-Making (MCDM) models to help organizations prioritize barriers and interventions through consideration of urgency, cost and impact-based criteria. This would complement the theoretical framework by combining qualitative hierarchy, quantitative validation, and pragmatic prioritization.

6.2. Practical implications

The results of this study demonstrate the need to address major challenges to the adoption of AI chatbots through deliberate and comprehensive organization strategy. Organizations can solve the most basic problems such as data privacy and compliance providing assurance to the users and thus allowing for speedy implementation. Organizations can then later look at other major barriers to a lack of acceptance and use of the new technology. In addition, more willingness to accept AI chatbots from employees will result from their immersion in training programs, which will promote a culture of innovation and reduce unease on the adoption of AI chatbots. In addition, stakeholder engagement is a pre-requisite for the success of AI implementation. Involving employees, technology providers, and regulators in the implementation gives a more integrated, multi-faceted approach to the different needs and concerns. To lead that initiative strategic planning should be preceded by a clear cost-benefit analysis to affect a balance between costs and the benefit of AI integration. Through these practical solutions firms can work to enhance the chances of successfully deploying the chatbot and thus improving user interaction and efficiency in business processes.

Finally, to operationalize these theoretical insights, enterprises can apply ranking and prioritization techniques based on Multi-Criteria Decision-Making (MCDM) models— (e.g., AHP or TOPSIS) that reflect the severity/feasibility of addressing barriers or their strategic implications. When combined with SEM results, the MCDM approaches help management invest the resources into the critical challenges for AI chatbot adoption initiatives leading to a more effective and successful acceptance rates.

In sum, a combination of trust-building, training, stakeholder engagement, strategic planning, and evidence-based prioritization tools can significantly increase the likelihood of successful chatbot deployment and ultimately improve user interaction, employee productivity, and business efficiency.

7. Conclusion and future research directions

The present study examines the barriers to AI chatbot adoption among working accounting and finance professionals. With the application of two methods, i.e., Interpretive Structural Modeling (ISM) and Structural Equation Modeling (SEM), the study reveals and categorizes eight key barriers, and further directs that how these barriers influence and accumulate over the adoption process (Rajan et al., 2021; Yadav et al., 2022; Zhao et al., 2024). The findings highlight the importance for organizations to develop a broad-based approach to foundational areas like data protection and compliance while encouraging user trust and engagement. Such insights can assist organizations to redefine AI integration challenges, optimize operational performance levels, and optimize user experiences.

However, the study suffers from certain limitations. First, it is a domain specific study (i.e. accounting and finance), therefore the findings may not be generalizable to any other context or domain experiencing the same issues. Second, the use of self-reported information will have led to some biases with respect to attitudes towards AI technologies (Kelly et al., 2023; Renz et al., 2024; Tubadji et al., 2021). Moreover, with the current pace of technology development the identified obstacles will be or may already have been shifted, what highlights the importance of ongoing research. Despite the usefulness of ISM and SEM for establishing strong foundations, they tend to facilitate a simplistic view of the reality in real organizational settings (Raut et al., 2018; Yenugula et al., 2023). Future research may explore barriers in the different sectors and particularly role of the stakeholders to promote adoption.

Ethics

The study involved human participants for data collection. The participants were assured of the confidentiality of their responses and informed consent was obtained from all the participants. The present study was approved by ethical committee bearing ID: UTAS-Muscat/BS/RIE/2025/24.

CRediT authorship contribution statement

Alaa Amin Abdalla: Writing – review & editing, Visualization, Supervision, Software, Resources, Project administration, Funding acquisition, Data curation. **Chandan Kumar Tiwari:** Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Data curation. **Mohd. Abass Bhat:** Writing – original draft, Visualization, Software, Methodology, Investigation, Data curation, Conceptualization. **Abhinav Pal:** Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Amir A. Abdulmuhsin:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration.

Declaration of competing interest

The authors state that none of their known financial conflicts or interpersonal connections appear to have an impact on the work described in this article. Thus, authors declare no conflicts of interest related to this study.

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Data availability

Data will be made available on request.

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