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# Modelling the barriers to AI-powered customer service adoption hierarchical structure: Fuzzy TISM and MICMAC analysis

**Abstract**
The adoption of AI-powered services in customer service is critical for organizational efficiency, yet consumer resistance remains a significant hurdle. While existing research has identified key barriers, the complex interrelationships between them are not well understood. This study identifies ten critical barriers namely Perceived Data Privacy Risk, Algorithmic Distrust, Perceived Lack of Transparency, Perceived Creepiness, Perceived Loss of Social Interaction, Lack of Human Touch, Perceived Usefulness, Perceived Ease of Use, Technology Anxiety, and Status Quo Bias. It employs Fuzzy Total Interpretive Structural Modelling (Fuzzy TISM) to structure these barriers into a hierarchical model interpreting the directional links. The barriers are categorized by MICMAC analysis according to their driving and dependence power. The results show that the two most basic and significant obstacles are perceived data privacy risk and algorithmic distrust, lack of human touch and perceived loss of social interaction are identified as high-dependent outcome-level barriers. The study concludes that unless the fundamental problems of trust and data privacy are thoroughly addressed, first managerial efforts aimed only at promoting usefulness and ease of use will be ineffective. This research provides a validated strategic roadmap for practitioners and contributes a novel hierarchical model to the theoretical discourse on technology adoption.

**Keywords:** AI Adoption, Customer Service, Fuzzy TISM, MICMAC Analysis, Chatbots, Consumer Resistance, Hierarchical Model, Interpretive Structural Modelling.

**JEL Code**: C65; O33; M15; M31; C63

## 1. Introduction

The customer service landscape is undergoing a profound transformation with the integration of Artificial Intelligence (AI) for enabling rapid, scalable and personalized interactions (McKinsey & Company, 2025). AI-powered services, including chatbots, automated routing systems, virtual assistants, and AI-driven recommendation engines, promise 24/7 availability, instant responses, and reduced operational costs (Chung *et al.*, 2020). However, despite these advantages, a significant 'adoption gap' persists. Many consumers remain hesitant, frustrated, or outright resistant to interacting with AI for service-related issues (Castelo, Bos, & Lehmann, 2019). In addition, companies are often struggling to change, interpret or translate the AI investments into sustainable adoption and value in customer service operations (McKinsey & Company, 2025; Mazuruse *et al.*, 2026). Adoption is regulated not only by technical capability but by complex web of organizational, regulatory, human, and market barriers that interact across various decision-making levels (Hassan *et al.*, 2025).

The application of Total Interpretive Structural Modelling (TISM), along with fuzzy set methods and Matriced Impacts Croisées-Multiplication Appliquée à un Classement (MICMAC), allows a more transparent and thorough method of capturing calculatedly the structured links among defined barriers and to stratify them by pushing and dependence power (Ahmad *et al.*, 2024). The Fuzzy adaptations of the TISM-MICMAC framework include specialist evaluation under vagueness and have seen rising application across technology adoption sub-categories from industry 4.0 to *e*Health and sustainable procurement, showing their relevance for mapping multi-level, uncertain barrier and ecosystems (Das, 2023). In line with this, the application of fuzzy TISM-MICMAC framework barriers to AI-powered customer service adoption is essential because many constructs (managerial readiness, trust, explainability) are generally fuzzy, as many researchers may understand them with considerable differences and measured severity varies by context. A mathematical foundation which formalizes such vagueness, leading specialist linguistic judgement aggregation into defensible models that keep the uncertainty rather than forcing premature thresholds, has been defined in Fuzzy Set Theory (Zadeh, 1965).

Existing literature, rooted in technology acceptance models like TAM (Davis, 1989) and UTAUT (Venkatesh *et al.*, 2003), has successfully cataloged a range of barriers to adoption, extending them with constructs like 'creepiness' (Luo *et al.*, 2019; Onohuean & Nyagadza, 2026), privacy concerns (Büschemann *et al.*, 2023), and trust (Ameen *et al.*, 2021). However, a critical literature gap exists: these studies largely treat these barriers as independent variables in regression-based models, failing to capture the complex, interdependent relationships between them (Sindhwani & Singh, 2022; Nyagadza *et al.*, 2025). The treatment of the barriers with fragmentation always risk overlooking the ways in which distal drivers such as regulation pressure and strategy of top management, navigate through tactical level processes and show as front line constraints which may be in form of agent acceptance and customer trust (Hoffman *et al.*, 2025). For a manager, knowing that 'privacy' and 'usefulness' are both important is insufficient; they need to know which lever to pull first. Does improving ease of use directly reduce perceived creepiness, or is the relationship more nuanced?

This study addresses this gap directly - the absence of a structured, causally integrated model of AI adoption barriers in customer service - by proposing and developing an integrated model using Fuzzy TISM and MICMAC analysis. Existing studies have catalogued barriers individually but have not modelled their interdependencies or hierarchical influence, leaving practitioners without actionable prioritization guidance. To fill this void, and grounded in innovation resistance and technology adoption literature alongside recent empirical studies of chatbot resistance and AI deployment challenges, the objectives are:

- *To identify the key barriers to AI-powered customer service adoption from the extant literature.*
- *To establish the contextual relationships between these barriers through expert judgment.*
- *To develop a hierarchical model (TISM) showing the sequence of influence and provide interpretive logic for the links.*
- *To incorporate fuzzy logic to handle ambiguity and subjectivity inherent in expert judgments.*
- *To classify the barriers into driver and dependent categories using MICMAC analysis to inform strategic prioritization.*

This article develops and validates barriers to AI-powered customer service adoption hierarchical model using the fuzzy TISM and fuzzy MICMAC analysis (Abdalla, 2025). Through the structured hierarchical explicit and quantified influence-dependence barriers, the proposed methodology assists decision makers focus interventions which aim at root causes rather than treating symptoms from the surface (Liu, 2025). In addition, the fuzzy TISM-MICMAC integrative application connects rigour of methodology with interpretable outline to practitioners, which is a vital requirement when policy developments are to be considered by the regulatory authorities, digital transformation leaders, and executives, responsible for AI governance in customer-facing obligations. The outcome of the current study, therefore, contributes to both theoretical advancement (through enhancing knowledge on customer service AI adoption barriers multi-levelled systemic nature such as perceived data privacy risk and algorithmic distrust, lack of human touch and perceived loss of social interaction) and professional practice development (incubation of a prioritized obstacle removal roadmap to scalable responsible AI deployment) (McKinsey & Company, 2025).

The remainder of this article is structured as follows; the first section presents a literature review, hypotheses, and the development of the research conceptual model. A section on methods follows, and then the analysis of results is presented. Discussions, conclusions, practical and theoretical implications, study limitations and future research directions are also presented.

## 2. Literature Review and Identification of Barriers

### 2.1 AI Powered customer service

Contemporary research highlights the impact of AI services and the massive role they play in changing the landscape of customer service completely (Luo *et al*., 2019a; Novak & Hoffman, 2019). The existing literature was also emphasized that AI alone cannot replace the human agents entirely, Instead, it is there to automate routine and repetitive tasks eyeballing human to focus on complex problem-solving and emotional higher-level interactions that require empathy and deeper understanding (Blut, Wang, *et al*., 2021; Samuelson & Zeckhauser, 1988). The optimal customer service experience is the outcome from a balanced integration of human expertise and technological capabilities. Such hybrid approach leverages the machine's efficiency while preserving the human's qualities (Kim & Kankanhalli, 2009; Samuelson & Zeckhauser, 1988). While The future is going into more sophisticated interactions, powered by multimodal interactions, emotional AI and seamless human-AI collaboration, the question remains, what is the logic behind customers preference or avoidance of AI powered customer service agents and therefore whether they will be succussed or not.

### 2.2 Barriers to AI based customer service adoption

Whenever AI is used for customer service purposes, a set of interrelated barriers come on the way. The following subsections review the empirical and theoretical foundations for each barrier, emphasizing how prior work collectively informs the design of the current study's hierarchical modelling approach rather than treating each barrier in isolation (Xie & Tsang, 2025).

#### 2.2.1 Perceived Data Privacy Risk

Customers express concerns about how AI services collect, store, and process their data and perhaps share their personal information, which stands in the way of adoption (Büschemann *et al*., 2023) . This barrier is justified by the Privacy Calculus Theory. This theory suggests that when customers compare privacy risks against potential benefits, they will always give privacy higher importance. In this case, AI requires users to share an extensive amount of data, so when this theory is applied, the outcome will not be in the best interest of AI agents at all. Machine learning, which is the technology AI agents are powered by, has a "black box" nature, which means that data flows are not transparent and are limited compared to traditional digital services. Since customers cannot trace how their data is being treated, this causes more resistance to AI systems as a replacement for simple rule-based automation. It is also important to note that different cultures, different industries, and different age groups all matter in this barrier, specifically because younger users do not care about their data privacy as much as older users and not all industries care about data privacy as much as finance and healthcare, for example.

### 2.2.2 Algorithmic Distrust

Another barrier is the overall lack of confidence in AI's ability to properly address issues, the complex ones in particular. And its ability to provide the customer with the most appropriate answer to their needs (Ameen *et al.* 2021; Castelo *et al.* 2019). Customers are in doubt about whether they can fully trust AI and if it is competent enough to solve their complex problems. The technology acceptance model provides a theoretical explanation for this barrier. It is proposed that when customers doubt competence, they consider it less useful, which directly inhibits adoption issues. According to Ameen *et al.* (2021) performance risk was highlighted as a barrier because customers believe that AI agents cannot manage to deliver outcomes in the required tasks. Castelo *et al.* (2019) showcased that people will quickly lose their trust in algorithms when they fail them, even after outperforming humans on average. Subjective tasks, which are typical in customer service, are the ones facing this disfavor the most. Excelling at routine queries and struggling with edge cases and contextual, ambiguous requests creates what is called the "competence paradox." In simple words, if customers cannot predict the success of any new technology, they will resist it.

### 2.2.3 Perceived Lack of Transparency (Opacity)

Customers in general need more transparency to trust AI. The more customers are aware of how AI came to conclusions and provided them with answers, the more they will be able to trust it (Shin 2021; Zhang & Wang 2022). Therefore, the lack of opacity is the third barrier. It is clearly stated in (Shin, 2021) that if a user can explain how AI comes to conclusions, they will be more able to trust it, which was also mentioned in (Zhang & Wang 2022) who demonstrated that when customers know how a result is obtained, their trust and satisfaction of the AI tool will automatically increase, which causes a lot of opaque AI agents to be used less (Araujo, 2018). AI agents cannot answer with "why" they came up with certain outcomes, which is the opposite of human agents, who can provide reasons and explain through dialogue. If a source of information cannot justify itself, then its users will not be able to develop. It all depends on how sensitive the topic in question is. When it comes to medical advice or financial guidance, users need to know exactly why they have received such an answer, which is not the case with simpler things like product recommendations.

### 2.2.4 Perceived Creepiness

Some customers reported a sense of unease and creepiness when they realized that AI agents know far too much personal information about them; they considered this feeling as one of the barriers to using this technology (Luo *et al.*, 2019; Novak & Hoffman 2019). This discomfort can be explained by the privacy boundary theory and the concept of contextual integrity (Nissenbaum, 2004). The more AI is personalised to suit specific users and knows more information about them and can recall the details quickly, the more unnatural and threatening it feels to engage with it. The more a culture is preserved, the stronger this feeling of intimidation becomes.

### 2.2.5 Perceived Loss of Social Interaction

Studies also showed that social interaction is a crucial part of any customer service interaction and that the lack of human empathy, emotional support, and social cues during an interaction enlarged the gap between customers and AI agents (Schanke *et al.*, 2021; Sheehan *et al.*, 2020).The social presence theory mentioned in Short *et al.* (1976) explains this barrier really well, because computers are only acting socially, and when people apply social rules to them, they will immediately notice their limitations, which therefore causes less adaptation (Castillo et al., 2021). Emotional intelligence is a core component of any successful customer service interaction; the lack of emotional intelligence in computers significantly impacts on the customers' satisfaction rates. In Sheehan *et al.* (2020), it is clearly mentioned that customers will not reach out to AI agents when they need emotional support and will always prefer human agents to solve their issues faster. Rational and emotional dimensions are required, especially when customers are upset, confused, and seeking emotional support even more than a pure solution. Lacking the subjective experience is what causes AI agents to be unable to provide authentic empathy (Wirtz *et al.*, 2018).

### 2.2.6 Lack of Human Touch

When a customer is reaching out for help, they do not simply ask for facts or a direct solution; they need someone who can fully interact and understand their nuance, sarcasm, and complex emotions and therefore provide them with the response they need to hear (Blut *et al.*, 2021; Chung *et al.*, 2020). This can be justified by the richness of human language processing and the Communication Accommodation Theory (Grice 1975). Even though AI technologies have advanced a lot, they are still very dependent on the contextual aspect of the meaning. The more customers need to make cognitive efforts to communicate a request, the harder it is to adopt, especially when tackling complicated and unclear topics. This barrier is more obvious in straightforward inquiries, such as tracking orders and checking balances, compared to advisory interactions like troubleshooting or providing recommendations.

### 2.2.7 Perceived Usefulness (as a barrier)

When a human agent is compared with an AI one, customers will always prefer the human because they simply believe and trust them more (Blut *et al.*, 2021). The lack of trust comes from disbelieving that AI is useful and able to entirely solve the problem. Therefore, when perceived usefulness is low, the possibility of adoption becomes more likely. As mentioned in the expectancy-value theory, adaptation only happens with the belief that technology exists (Fishbein & Ajzen, 1975). Unlike many barriers that might be biased or irrational, this barrier is based on customers' experiences, such as the Capability-Expectation Mismatch, when customers use the wrong tool for their need. Second, the Capability-Expectation Mismatch, which means providing quick but shallow answers. Third, the Comparative Benchmark Problem, when customers compare AI to humans in customer service. Fourth, the outcome uncertainty: unlike dealing with humans, having a conversation with an AI agent cannot ensure certainty. Lastly, the sunk cost asymmetry: multiple failures mean more time wasted, which leaves the customer with a poor impression of the technology.

### 2.2.8 Perceived Ease of Use

The cognitive efforts needed to interact with an AI agent are much more than interacting with a human, which makes it another reason to back off (Blut *et al.* 2021; Samuelson & Zeckhauser, 1988). Having to invest higher cognitive efforts to interact with AI, which is not the case with dealing with a human agent. This barrier aligns with Cognitive Load Theory and the principle of least effort. Blut *et al.* (2021) found that customers experience higher cognitive effort with AI agents because they need to structure their queries precisely, which will make them work harder, and that is the opposite of why AI agents were introduced in the first place. For older adults, the cognitive effort barrier is higher than for younger ones, considering their limited use of technology to begin with.

### 2.2.9 Technology Anxiety

The fact that not everyone is tech savvy in general is also a barrier (Chung *et al.*, 2020; Grice 1975). Lacking technology readiness and digital skills affects customers' confidence in using the technology effectively. Feeling less confident creates a demographic adoption barrier. Low technology readiness leads to avoiding any automated service channel.

### 2.2.10 Status Quo Bias

Being used to something and not wanting to try something new, also referred to as "Status Quo Bias," is also an obstacle (Kim & Kankanhalli, 2009; Samuelson & Zeckhauser, 1988). Status Quo Bias Theory discusses how people prefer existing states instead of trying something new due to uncertainty and transition costs, and when it comes to adopting a new technology like AI in customer service, this will come as resistance to changing current habits (Kim & Kankanhalli, 2009). Another factor that contributes to this uncertainty is that human agents have a long relationship with customers who are satisfied and used to it, which makes it harder for them to make the shift. Customers stop thinking objectively and tend to be biased by their previous successful experiences.

These above constructs are well-established in information systems and consumer behavior literature and have been summarized in Table 1.

**Table 1:** Key Barriers to AI-Powered Customer Service Adoption

| Sl. No | Barriers | Description | References |
|---|---|---|---|
| B1 | Perceived Data Privacy Risk | The consumer fear that their personal data shared with the AI will be misused, stored insecurely, or sold. | (Büschemann et al., 2023; Gao, 2023) |
| B2 | Algorithmic Distrust | The lack of confidence in the AI's ability to understand complex queries, provide accurate information, and act in the user's best interest. | (Ameen, Hosany, et al., 2021; Castelo et al., 2019) |
| B3 | Perceived Lack of Transparency (Opacity) | The "black box" nature of AI, where the user cannot comprehend how the AI arrived at a specific decision or response. | (Shin, 2021; Zhang & Wang, 2022) |
| B4 | Perceived Creepiness | The feeling of unease or eeriness when an AI demonstrates seemingly too much knowledge about the user's personal life or behavior. | (Luo et al., 2019a; Novak & Hoffman, 2019) |
| B5 | Perceived Loss of Social Interaction | The dissatisfaction stemming from the absence of human empathy, emotional | (Schanke et al., 2021; Sheehan et al., 2020) |

| | | | |
|---|---|---|---|
| | | support, and social cues during an interaction. | |
| B6 | Lack of Human Touch | The inability of AI to understand nuance, sarcasm, complex emotions, and provide customized, empathetic solutions. | (Blut, Wang, et al., 2021; Chung et al., 2020) |
| B7 | Perceived Usefulness (as a barrier) | The belief that the AI service is not capable of solving the user's problem effectively or providing a better solution than a human agent. | (Blut, Wang, et al., 2021) |
| B8 | Perceived Ease of Use (as a barrier) | The belief that interacting with the AI is cognitively demanding, non-intuitive, or cumbersome. | (Blut, Wang, et al., 2021; Samuelson & Zeckhauser, 1988) |
| B9 | Technology Anxiety | A general fear or apprehension about using new technological systems. | (Heinonen, 2018; Laukkanen, 2016) |
| B10 | Status Quo Bias | A preference for the familiar method of interaction (i.e., human agents) due to comfort and habit. | (Kim & Kankanhalli, 2009; Samuelson & Zeckhauser, 1988) |

**Source:** Literature review (2025).

**3. Research Methodology**

This research employs a multi-method approach that is combining qualitative expert judgment with quantitative Fuzzy TISM followed by MICMAC analysis. It is a widely used technique in supply chain and other management functions to understand the key drivers and barriers of a phenomenon (Choudhury et al., 2021). The step-by-step process of this research is shown in Figure 1. Using an integrated Fuzzy TISM (Total Interpretive Structural Modeling) and MICMAC (Cross-Impact Matrix Multiplication Applied to Classification) framework is useful in describing an organized approach for examining the adoption barriers of AI-enabled service agents. The process starts with a review of the literature to explore and find out the main obstacles which were then discussed with a panel of experts to establish a contextual relationship. Experts have helped in determining the contextual connections among the barriers which are then further processed to prepare a Structural Self-Interaction Matrix (SSIM) and finally transformed into an Initial Reachability Matrix (IRM).

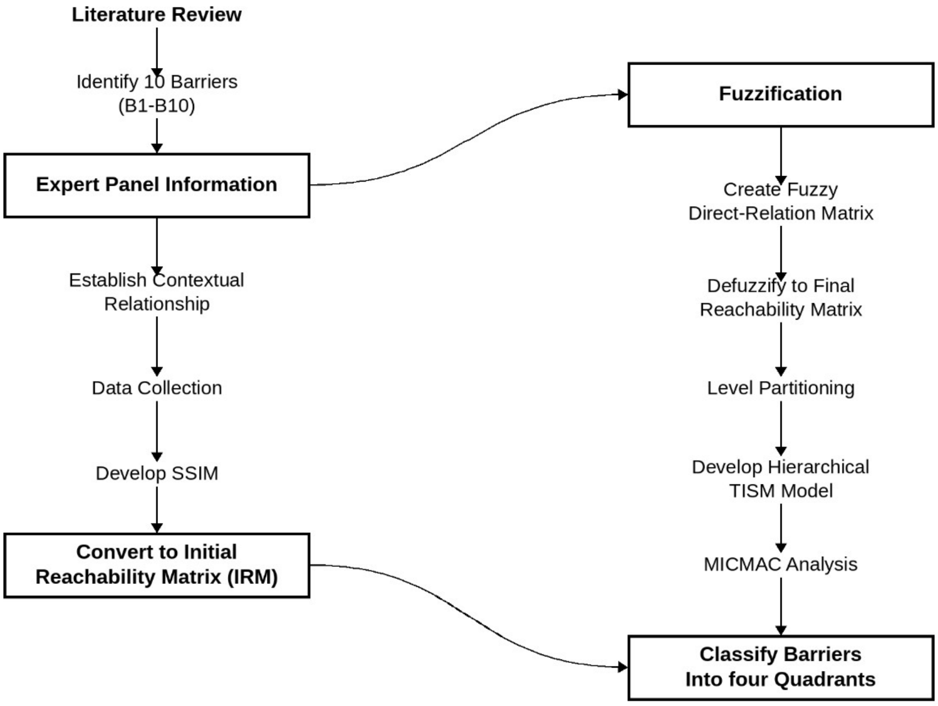



**Figure 1:** Research Methodology Flowchart
**Source:** Authors' conception (2025).

Fuzzification which converts subjective expert judgments into a Fuzzy Direct-Relation Matrix to handle uncertainty and ambiguity inherent in human assessment is a key component of this approach. After that a Final Reachability Matrix is created by defuzzifying this matrix providing data that is understandable and useful. Level partitioning is then used to create a hierarchical TISM model that shows the layered structure of influence among the barriers by graphically arranging them according to their driving and dependence power (Zhang *et al.*, 2021). Lastly, based on their driving and dependence scores a MICMAC analysis divides the obstacles into four different quadrants: autonomous dependent linkage and independent/driving. This classification offers a potent dual-faceted understanding of the ecosystem of adoption challenges by assisting researchers and practitioners in differentiating between outcome barriers that are influenced by others and root cause barriers that necessitate strategic intervention. These combined methods are useful in linking barriers in emerging technologies with adequately balanced qualitative knowledge and quantitative processes which is providing both strategic clarity and interpretive depth (Singhal *et al.*, 2022).

### 3.1 Expert Panel Formation

A panel of 10 experts was formed to ensure a holistic perspective based on the established TISM protocols (Patrício & Ferreira, 2021; Singhal *et al.*, 2022). Experts were recruited through purposive sampling based on strict criteria: academics required ≥8 years research experience with relevant publications; practitioners required ≥10 years in CX/digital transformation with AI deployment experience; lead users required ≥5 years frequent interaction with AI customer service agents. From 18 candidates, 10 were selected to ensure balanced representation (3 academics, 2 practitioners, 5 lead users).

To ensure consensus and reduce individual bias, we employed a two-round Delphi-inspired approach. In round 1, experts individually completed the V/A/X/O assessments. Kendall's Coefficient of Concordance (W) was calculated to measure agreement, yielding W = 0.62 ($p < 0.01$), indicating moderate consensus. In round 2, a moderated workshop resolved disagreements through discussion, after which Kendall's W improved to 0.81 ($p < 0.001$), indicating strong consensus. The final SSIM (Table 3) reflects this refined agreement. This process aligns with established TISM practices (Okoli & Pawlowski, 2004; Singhal et al., 2022). The panel consists of the following experts:

**Table 2:** Expert Panel Composition

| Expert Group | Number | Profile Description | Rationale |
|---|---|---|---|
| **Academic Researchers** | 3 | Professors have specializations in Consumer Behavior, Information Systems and Service Marketing. | Provide theoretical grounding and ensure construct validity. |
| **Industry Practitioners** | 2 | Customer Experience (CX) Manager and Digital Transformation Executive from IT Company and a leading bank. | Provide practical, real-world insights into consumer pain points. |
| **Lead Users** | 5 | Consumers who frequently use digital services and have experience with AI customer services agents. | Provide the end-user perspective and validate the experiential factors. |

**Source:** Authors' conception (2025).

**Data Collection Procedure:** Data collection was conducted in two phases between October and December 2025.

In Phase 1 (Pre-workshop), selected experts received a detailed information package via email, including: (a) a briefing document explaining the study objectives and barrier definitions (Table 1); (b) a structured Excel workbook containing all 45 pairwise comparisons; and (c) the fuzzy linguistic scale (Table 5) with clear instructions. Experts independently completed the workbook within two weeks, recording their judgments for each relationship using the V/A/X/O coding scheme (for SSIM) and the linguistic scale (for fuzzy direct relationships). Completed workbooks were returned via encrypted email.

In Phase 2 (Consensus Workshop), a three-hour moderated online workshop was conducted via Zoom. The session began with a presentation of aggregated Phase 1 results, highlighting areas of agreement and disagreement. Guided by the moderator, experts engaged in structured discussion for relationships where consensus was lacking, sharing rationales based on their expertise. After discussion, experts individually re-recorded their judgments. The final consensus was used to construct the SSIM (Table 3) and the aggregated fuzzy direct relationship matrix (Table 6). All responses were anonymized during aggregation to reduce social desirability bias.

### 3.2 Establishing Contextual Relationship and Developing SSIM

The contextual relationship for this study was defined as: "Barrier i influences or aggravates Barrier j." In a series of moderated sessions, the expert panel was presented with all pairwise combinations of the ten barriers. For each pair (i, j), they were asked to reach a consensus on the nature of the relationship using the following codes (Kumar & Gupta, 2021):

V: Barrier i influences barrier j.

A: Barrier j influences barrier i.

X: Barrier i and j influence each other (a two-way relationship).

O: Barriers i and j are unrelated.

The consolidated SSIM is presented in Table 3.

**Table 3:** Structural Self-Interaction Matrix (SSIM)

| **Barriers AI-Powered Customer Service Adoption** | **B10** | **B9** | **B8** | **B7** | **B6** | **B5** | **B4** | **B3** | **B2** |
|---|---|---|---|---|---|---|---|---|---|
| Perceived Data Privacy Risk (B1) | V | V | V | V | V | V | V | V | V |
| Algorithmic Distrust (B2) | V | V | V | V | V | V | X | V | - |
| Perceived Lack of Transparency (Opacity) (B3) | V | A | A | A | A | A | V | - | |
| Perceived Creepiness (B4) | A | A | A | A | V | V | - | | |
| Perceived Loss of Social Interaction (B5) | O | O | O | O | X | - | | | |
| Lack of Human Touch(B6) | O | O | O | O | - | | | | |
| Perceived Usefulness (as a barrier) (B7) | A | A | A | - | | | | | |
| Perceived Ease of Use (as a barrier) (B8) | A | A | - | | | | | | |
| Technology Anxiety (B9) | X | - | | | | | | | |
| Status Quo Bias (B10) | - | | | | | | | | |

**Source:** Literature review (2025).

| **Relationship** |
|---|
| B1 influences all others |
| B2 influences B3-B10, has mutual relationship with B4 |
| B3 influences B4, is influenced by B7-B9 |
| B4 influences B5&B6, is influenced by B7-B9 |
| B5 and B6 influence each other |
| B6 is not a driver for B1-B5, B7-B10 |
| B7 is influenced by B8-B10 |
| B8 is influenced by B9&B10 |
| B9 and B10 influence each other |

**Source:** Literature review (2025).

### 3.3 Initial Reachability Matrix (IRM) and Linguistic Scale

The SSIM was converted into a binary Initial Reachability Matrix (IRM) by replacing V, A, X, and O with 1 and 0 as per the replacement criteria suggested by (Barve et al., 2009). The SSIM is converted into a binary matrix known as the initial reachability matrix: if the (i, j) entry in the SSIM is V, then the (i, j) item in the reachability matrix is transformed into 1 and the (j, i) entry becomes 0 if the (i, j) entry in the SSIM is A, then the (i, j) item in the reachability matrix is transformed into 0 and the (j, i) entry becomes 1 if the (i, j) entry in the SSIM is X, then the (i, j) item in the reachability matrix is transformed into 1 and the (j, i) entry becomes 1 if the (i, j) entry in the SSIM is O, then the (i, j) item in the reachability matrix is transformed into 0 and the (j, i) entry becomes 0.

**Table 4:** Initial Reachability Matrix (IRM)

| **Barriers AI-Powered Customer Service Adoption** | **B1** | **B2** | **B3** | **B4** | **B5** | **B6** | **B7** | **B8** | **B9** | **B10** |
|---|---|---|---|---|---|---|---|---|---|---|
| Perceived Data Privacy Risk (B1) | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Algorithmic Distrust (B2) | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Perceived Lack of Transparency (Opacity) (B3) | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 |
| Perceived Creepiness (B4) | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| Perceived Loss of Social Interaction (B5) | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 |
| Lack of Human Touch(B6) | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 |
| Perceived Usefulness (as a barrier) (B7) | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 0 |
| Perceived Ease of Use (as a barrier) (B8) | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 |
| Technology Anxiety (B9) | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 |
| Status Quo Bias (B10) | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 |

**Source:** Literature review (2025).

To incorporate the vagueness and varying strengths of influence, we employed fuzzy logic. Experts provided judgments on a linguistic scale, which were converted to Triangular Fuzzy Numbers (TFNs) (Jami Pour *et al.*, 2021). The scale used in this study is shown in the following table 5.

**Table 5:** Fuzzy linguistic scale and Triangular Fuzzy Numbers (TFNs)

| **Linguistic Term** | Abbreviation | Triangular Fuzzy Number (l, m, u) | Crisp Value (De-fuzzified) |
|---|---|---|---|
| No Influence | NI | (0.00, 0.00, 0.25) | 0.083 |
| Very Low Influence | VLI | (0.00, 0.25, 0.50) | 0.25 |
| Low Influence | LI | (0.25, 0.50, 0.75) | 0.5 |
| High Influence | HI | (0.50, 0.75, 1.00) | 0.75 |
| Very High Influence | VHI | (0.75, 1.00, 1.00) | 0.917 |

**Source:** Literature review (2025).

### 3.4 Aggregated Fuzzy direct relationship and defuzzified total relationship

Aggregated Fuzzy Direct Relationship Matrix (D) is presented in the following table 6 which represents the consolidated expert perception of direct causal influences among the studied factors under conditions of uncertainty, the experts are giving their evaluations using linguistic terms as shown in table 5.

**Table 6:** Aggregated Fuzzy Direct Relationship Matrix (Triangular Fuzzy Numbers)
**Source:** Literature review (2025).

| Barrier | B1 | B2 | B3 | B4 | B5 | B6 | B7 | B8 | B9 | B10 |
|---|---|---|---|---|---|---|---|---|---|---|
| B1 | (0,0,0.05) | (0.09,0.12,0.12) | (0.09,0.12,0.12) | (0.09,0.12,0.12) | (0.06,0.09,0.12) | (0.06,0.09,0.12) | (0.09,0.12,0.12) | (0.09,0.12,0.12) | (0.09,0.12,0.12) | (0.09,0.12,0.12) |
| B2 | (0,0,0.05) | (0,0,0.05) | (0.06,0.09,0.12) | (0.09,0.12,0.12) | (0.06,0.09,0.12) | (0,0,0.05) | (0.09,0.12,0.12) | (0.06,0.09,0.12) | (0.09,0.12,0.12) | (0.09,0.12,0.12) |
| B3 | (0,0,0.05) | (0,0.03,0.06) | (0,0,0.05) | (0.06,0.09,0.12) | (0.03,0.06,0.09) | (0.03,0.06,0.09) | (0.03,0.06,0.09) | (0.03,0.06,0.09) | (0.03,0.06,0.09) | (0.06,0.09,0.12) |
| B4 | (0,0,0.05) | (0.06,0.09,0.12) | (0.03,0.06,0.09) | (0,0,0.05) | (0.06,0.09,0.12) | (0.06,0.09,0.12) | (0.03,0.06,0.09) | (0.03,0.06,0.09) | (0.03,0.06,0.09) | (0.03,0.06,0.09) |
| B5 | (0,0,0.05) | (0,0,0.05) | (0.03,0.06,0.09) | (0.03,0.06,0.09) | (0,0,0.05) | (0.09,0.12,0.12) | (0,0,0.05) | (0,0,0.05) | (0,0,0.05) | (0,0,0.05) |
| B6 | (0,0,0.05) | (0,0,0.05) | (0.03,0.06,0.09) | (0.03,0.06,0.09) | (0.09,0.12,0.12) | (0,0,0.05) | (0,0,0.05) | (0,0,0.05) | (0,0,0.05) | (0,0,0.05) |
| B7 | (0,0,0.05) | (0,0,0.05) | (0.06,0.09,0.12) | (0.06,0.09,0.12) | (0,0,0.05) | (0,0,0.05) | (0,0,0.05) | (0.03,0.06,0.09) | (0.03,0.06,0.09) | (0.03,0.06,0.09) |
| B8 | (0,0,0.05) | (0,0,0.05) | (0.06,0.09,0.12) | (0.06,0.09,0.12) | (0,0,0.05) | (0,0,0.05) | (0.06,0.09,0.12) | (0,0,0.05) | (0.03,0.06,0.09) | (0.03,0.06,0.09) |
| B9 | (0,0,0.05) | (0,0,0.05) | (0.06,0.09,0.12) | (0.06,0.09,0.12) | (0,0,0.05) | (0,0,0.05) | (0.06,0.09,0.12) | (0.06,0.09,0.12) | (0,0,0.05) | (0.09,0.12,0.12) |
| B10 | (0,0,0.05) | (0,0,0.05) | (0.06,0.09,0.12) | (0.06,0.09,0.12) | (0,0,0.05) | (0,0,0.05) | (0.06,0.09,0.12) | (0.06,0.09,0.12) | (0.09,0.12,0.12) | (0,0,0.05) |

The expert judgments, collected using the linguistic scale in Table 5, were converted into Triangular Fuzzy Numbers (TFNs) and aggregated across all 10 experts using the arithmetic mean. The resulting **Aggregated Fuzzy Direct Relationship Matrix** is presented in Table 6, where each cell (l, m, u) represents the consensus fuzzy score for the direct influence of barrier i on barrier j.

**Table 7:** Defuzzified Total Relationship Matrix (Crisp Values)

| **Barrier** | **B1** | **B2** | **B3** | **B4** | **B5** | **B6** | **B7** | **B8** | **B9** | **B10** | **$R_i$ (Sum Rows)** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Perceived Data Privacy Risk (B1) | 0.12 | 0.85 | 0.87 | 0.88 | 0.68 | 0.68 | 0.82 | 0.83 | 0.85 | 0.86 | 7.44 |
| Algorithmic Distrust(B2) | 0.05 | 0.08 | 0.72 | 0.84 | 0.64 | 0.58 | 0.78 | 0.73 | 0.81 | 0.82 | 6.05 |
| Perceived Lack of Transparency (Opacity) (B3) | 0.04 | 0.22 | 0.18 | 0.65 | 0.42 | 0.42 | 0.48 | 0.45 | 0.48 | 0.62 | 3.96 |
| Perceived Creepiness(B4) | 0.05 | 0.58 | 0.42 | 0.28 | 0.68 | 0.68 | 0.48 | 0.45 | 0.48 | 0.52 | 4.62 |
| Perceived Loss of Social Interaction(B5) | 0.03 | 0.12 | 0.32 | 0.35 | 0.22 | 0.78 | 0.28 | 0.25 | 0.28 | 0.28 | 2.91 |
| Lack of Human Touch(B6) | 0.03 | 0.12 | 0.32 | 0.35 | 0.78 | 0.22 | 0.28 | 0.25 | 0.28 | 0.28 | 2.91 |
| Perceived Usefulness (as a barrier) (B7) | 0.03 | 0.15 | 0.58 | 0.62 | 0.28 | 0.28 | 0.18 | 0.38 | 0.42 | 0.45 | 3.37 |
| Perceived Ease of Use (as a barrier) (B8) | 0.03 | 0.18 | 0.65 | 0.68 | 0.32 | 0.32 | 0.58 | 0.22 | 0.48 | 0.52 | 3.98 |
| Technology Anxiety(B9) | 0.04 | 0.22 | 0.72 | 0.75 | 0.38 | 0.38 | 0.68 | 0.65 | 0.28 | 0.78 | 4.88 |
| Status Quo Bias(B10) | 0.04 | 0.22 | 0.75 | 0.78 | 0.38 | 0.38 | 0.72 | 0.68 | 0.78 | 0.28 | 5.01 |
| $C_j$ (Sum Columns) | 0.46 | 2.78 | 5.95 | 6.18 | 4.58 | 4.52 | 5.28 | 4.89 | 5.74 | 5.51 | Total: 45.13 |

**Source:** Literature review (2025).

The aggregated fuzzy matrix (Table 6) was defuzzified using the Center of Area method with the formula (l + 2m + u)/4 (Jami Pour et al., 2021). This produced the crisp direct relationship matrix D shown in Table 7, which quantifies the direct influence between each pair of barriers

**Section 3.4.2: Total Relationship Matrix**

To capture both direct and indirect influences between barriers, the defuzzified direct relationship matrix **D** (Table 7) was transformed into a total relationship matrix **T** using the DEMATEL-based procedure (Ahmad et al., 2024).

**Step 1: Normalization.** The normalization factor *k* was calculated as the maximum of the row sums of matrix **D**:

$$k = \max_{1 \le i \le n} \sum_{j=1}^{n} d_{ij} = 7.44$$

The normalized direct relationship matrix **N** was then obtained by multiplying each element of **D** by 1/*k*:

$$N = \frac{1}{k} \times D$$

**Step 2: Total Relationship Matrix.** The total relationship matrix **T**, which accounts for both direct and indirect effects, was computed using the matrix algebra formula:

$$T = N(I - N)^{-1}$$

where **I** is the identity matrix. The convergence condition $\lim_{m \to \infty} N^m = 0$ was verified, ensuring the validity of the matrix inversion (i.e., that the infinite series $N + N^2 + N^3 + ...$ converges to $N(I - N)^{-1}$).

The resulting total relationship matrix **T** is presented in Table 8.

### 3.5 Final Reachability Matrix

To prepare the final reachability matrix a threshold value (α) is used to filter out weak or negligible relationships from the defuzzified total relationship matrix (T) and to retain only meaningful and influential causal relations for structural modeling. The threshold value was calculated as the mean of all elements in the defuzzified total relationship matrix, resulting in $\alpha = 0.4513$. Finally, the relationships having values greater than or equal to α are retained (coded as 1) and values below α are considered as insignificant and removed (coded as 0). The final reachability matrix thus obtained is shown in Table 8 below.

The final reachability matrix reveals that barriers related to trust, privacy, and system transparency (B1–B3) exhibit relatively high driving power, indicating their foundational role in shaping user perceptions toward AI-based customer service. In contrast, behavioral and attitudinal barriers such as technology anxiety (B9) and status quo bias (B10) show higher dependence power, suggesting that they primarily emerge as consequences of unresolved technical and perceptual concerns. This pattern implies that addressing privacy, reliability, and transparency issues can indirectly reduce user resistance and habitual preference for human agents.

**Table 8:** Final Reachability Matrix

| **Barrier** | **B1** | **B2** | **B3** | **B4** | **B5** | **B6** | **B7** | **B8** | **B9** | **B10** |
|---|---|---|---|---|---|---|---|---|---|---|
| Perceived Data Privacy Risk (B1) | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Algorithmic Distrust(B2) | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Perceived Lack of Transparency (Opacity) (B3) | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 1 |
| Perceived Creepiness(B4) | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 1 |
| Perceived Loss of Social Interaction(B5) | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| Lack of Human Touch(B6) | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| Perceived Usefulness (as a barrier) (B7) | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Perceived Ease of Use (as a barrier) (B8) | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 1 |
| Technology Anxiety (B9) | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 1 |
| Status Quo Bias(B10) | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 0 |

**Source:** Literature review (2025).

### 3.6 Level partitioning

Level partitioning is a systematic step which is used to organize barriers into a clear hierarchical structure based on their driving and dependence relationships. With the help of the final reachability matrix, the reachability set (R) and the antecedent set (A) are identified for each barrier. A barrier is assigned a level when its reachability set is the same as its intersection with the antecedent set which indicates that it does not lead to any other remaining barriers, once a level is identified the corresponding barriers are removed and the process is repeated iteratively until all barriers are assigned levels.

**Table 9:** Iteration 1 - Level Identification

| Barrier | Reachability Set (R) | Antecedent Set (A) | Intersection (R∩A) | Level |
|---|---|---|---|---|
| Perceived Data Privacy Risk (B1) | 1,2,3,4,5,6,7,8,9,10 | 1 | 1 | - |
| Algorithmic Distrust (B2) | 2,3,4,5,6,7,8,9,10 | 1,2,4 | 2,4 | - |
| Perceived Lack of Transparency (Opacity) (B3) | 3,4,7,9,10 | 1,2,3,7,8,9,10 | 3,7,9,10 | - |
| Perceived Creepiness (B4) | 2,4,5,6,7,9,10 | 1,2,3,4,7,8,9,10 | 2,4,7,9,10 | - |
| Perceived Loss of Social Interaction (B5) | 5,6 | 1,2,4,5,6 | 5,6 | I |
| Lack of Human Touch (B6) | 5,6 | 1,2,4,5,6 | 5,6 | I |
| Perceived Usefulness (as a barrier) (B7) | 3,4,7 | 1,2,3,4,7,8,9,10 | 3,4,7 | - |
| Perceived Ease of Use (as a barrier) (B8) | 3,4,7,9,10 | 1,2,8,9,10 | 9,10 | - |
| Technology Anxiety (B9) | 3,4,7,8,10 | 1,2,3,4,8,9,10 | 3,4,8,10 | - |
| Status Quo Bias (B10) | 3,4,7,8,9 | 1,2,3,4,8,9,10 | 3,4,8,9 | - |

**Source:** Literature review (2025).

The above Table 9 shows the first iteration of the level partitioning carried out from the final reachability matrix. We repeated the iterations to ensure that each barrier is assigned to a level and the final level partitioning matrix thus obtained is depicted in Table 10.

**Table 10:** Final level partitioning

| Level | Barriers | Interpretation |
|---|---|---|
| I | B5, B6 | Top-level barriers - Most influenced by others |
| II | B7 | Secondary level |
| III | B3, B4 | Intermediate level |
| IV | B8, B9, B10 | Lower intermediate level |
| V | B2 | Lower level |
| VI | B1 | Bottom-level - Most driving barrier |

**Source:** Literature review (2025).

### 3.7 The Digraph

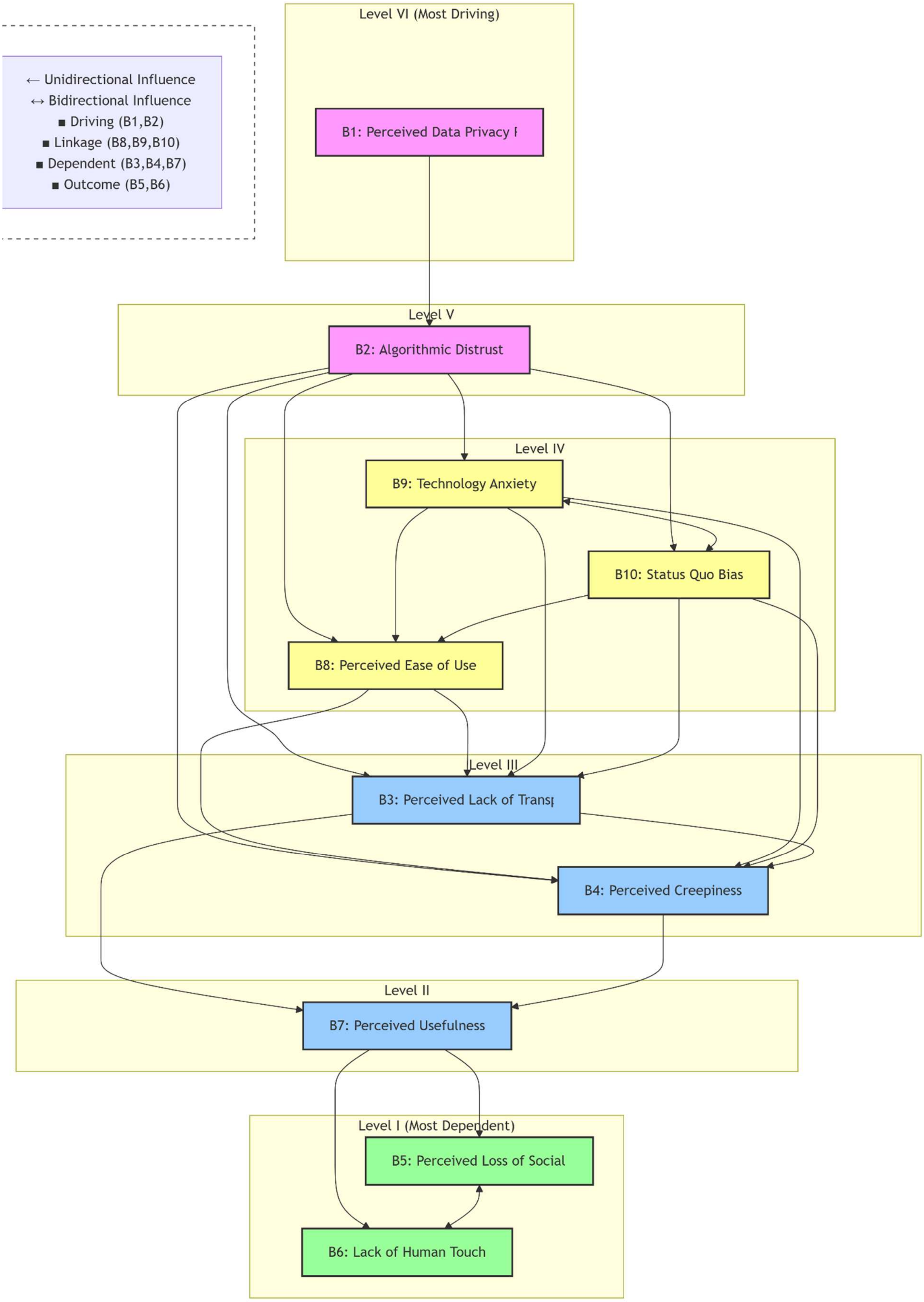
A digraph, or directed graph, is the final structural diagram used to visually map the causal relationships and hierarchical dependencies between the adoption barriers of AI-enabled service agents. It helps in translating the numerical data from the final reachability matrix into visual model where nodes represent the barriers and directed arrows show the influence pathways between them. This digraph as shown in fig 2 is showing the influence structure of 10 key barriers to adopting AI service agents which are organized into six levels from most dependent (top) to most driving (bottom).

The top levels (I and II) contain the most immediate, surface-level barriers for users. Level I: Perceived Loss of Social Interaction (B5) and Lack of Human Touch (B7) while Level II: Perceived Usefulness (B3) and Perceived Ease of Use (B6), these are highly dependent and largely influenced by other barriers below.

The middle levels (III and IV) include transitional barriers. Level III: Perceived Lack of Transparency (B4) and Technology Anxiety (B9) and Level IV: Status Quo Bias (B10) both influence barriers above and are influenced by those below.

The bottom levels (V and VI) hold the deepest root causes. Level V: Algorithmic Distrust (B2) and Level VI: Perceived Data Privacy Risk (B1), these are the strongest drivers which are influencing nearly all barriers.

The TISM model illustrates that perceived data privacy risk (B1) and lack of transparency (B3) directly contribute to algorithmic distrust (B2), which subsequently intensifies perceived creepiness (B4) and weakens perceived usefulness (B7). This causal chain suggests that when users are unable to understand how AI systems process their data, their confidence in automated decision-making diminishes. As a result, emotional discomfort and skepticism toward service quality increase, ultimately reinforcing technology anxiety (B9) and preference for human agents (B10). The model highlights that trust-building mechanisms and transparent system design are essential for mitigating downstream adoption barriers.



← Unidirectional Influence
↔ Bidirectional Influence
■ Driving (B1,B2)
■ Linkage (B8,B9,B10)
■ Dependent (B3,B4,B7)
■ Outcome (B5,B6)
Level VI (Most Driving)
B1: Perceived Data Privacy I
Level V
B2: Algorithmic Distrust
Level IV
B9: Technology Anxiety
B10: Status Quo Bias
B8: Perceived Ease of Use
Level III
B3: Perceived Lack of Transı
B4: Perceived Creepiness
Level II
B7: Perceived Usefulness
Level I (Most Dependent)
B5: Perceived Loss of Social
B6: Lack of Human Touch

Fig 2: Digraph of Barriers to AI-Enabled Service Agent Adoption Showing Hierarchical Levels and Interrelationships

**Source:** Literature review (2025).

**Note:** Bidirectional arrows (↔) indicate mutually reinforcing relationships at the same level. Unidirectional arrows (→) indicate directional influence. Barriers are color-coded by MICMAC classification: driving (purple), linkage (yellow), dependent (blue), and outcome (green).

**Justification of Same-Level Interrelationships**:

The digraph (Figure 2) presents barriers organized into six hierarchical levels based on their driving and dependence power from the level partitioning analysis (Table 10). An important consideration in interpretive structural modeling is whether barriers positioned at the same level exhibit direct relationships with one another. Based on our analysis and expert consensus, we provide the following justifications:

Level I (B5: Perceived Loss of Social Interaction; B6: Lack of Human Touch): These barriers demonstrate a bidirectional relationship (B5 ↔ B6) as confirmed in the SSIM (Table 3) and final reachability matrix (Table 8). The interpretive logic is that these barriers reinforce each other: the absence of social cues makes interactions feel mechanical (B5), while the lack of emotional depth reduces meaningful engagement (B6), creating a self-reinforcing cycle. This aligns with Communication Accommodation Theory (Grice, 1975) and prior empirical findings (Chung et al., 2020; Sheehan et al., 2020).

Level III (B3: Perceived Lack of Transparency; B4: Perceived Creepiness): Although positioned at the same intermediate level, these barriers do not exhibit a direct relationship in our model. The final reachability matrix (Table 8) shows B3 influences B4 (B3 → B4), but the reverse path (B4 → B3) is not supported. This unidirectional relationship is justified by the interpretive logic that when users cannot understand how AI reaches conclusions about them (B3), they attribute mysterious knowledge to invasive data practices, increasing discomfort (B4). However, feeling creeped out (B4) does not necessarily increase perceptions of opacity (B3); users may feel uneasy even when they understand how the system works.

Level IV (B8: Perceived Ease of Use; B9: Technology Anxiety; B10: Status Quo Bias): These linkage barriers exhibit complex interrelationships. The final reachability matrix confirms bidirectional relationships between B9 and B10 (B9 ↔ B10), indicating that anxiety reinforces preference for familiar channels, while status quo bias increases reluctance to engage, sustaining anxiety through lack of positive exposure, a vicious cycle consistent with Status Quo Bias Theory (Samuelson & Zeckhauser, 1988) and prior research (Kim & Kankanhalli, 2009; Laukkanen, 2016). However, B8 (Ease of Use) shows only unidirectional influences: it is influenced by B9 and B10 but does not directly influence them back at the same level, as confirmed by the reachability matrix.

Level V (B2: Algorithmic Distrust) and Level VI (B1: Perceived Data Privacy Risk): These driving barriers occupy distinct levels and show unidirectional influence from B1 to B2, consistent with Privacy Calculus Theory (Büschemann et al., 2023).

The structure reveals that addressing foundational issues like data privacy (B1) and algorithmic distrust (B2) is critical because they propagate influence upward, ultimately shaping user perceptions and emotional barriers at the top.

The TISM model reveals that perceived data privacy risk (B1) and lack of transparency (B3) act as foundational barriers that directly increase algorithmic distrust (B2). This distrust further intensifies perceived creepiness (B4) and weakens perceived usefulness (B7) and ease of use (B8). These cascading effects contribute to technology anxiety (B9) and ultimately reinforce status quo bias (B10). The directional relationships thus demonstrate that trust- and transparency-related concerns trigger broader emotional and behavioral resistance to AI-based customer service.

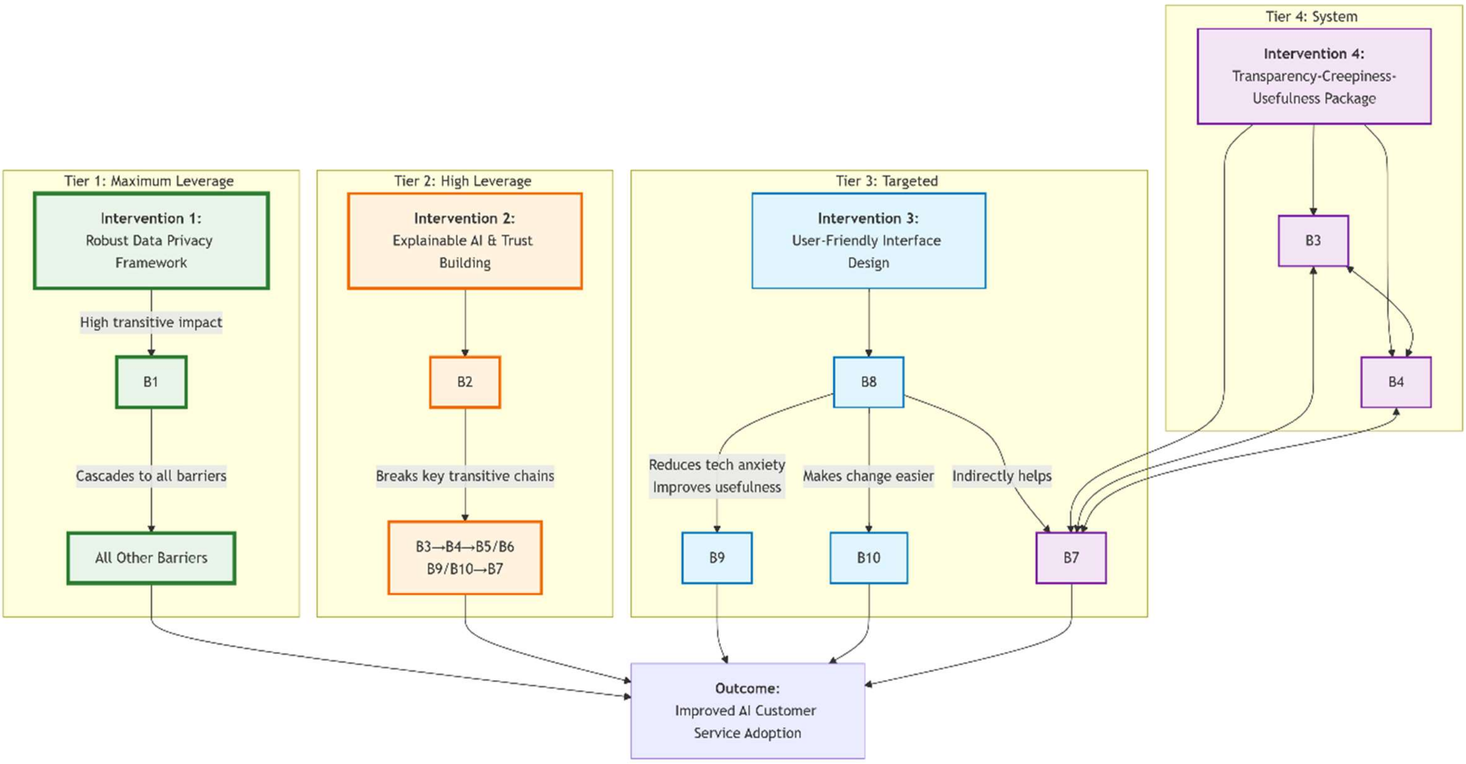


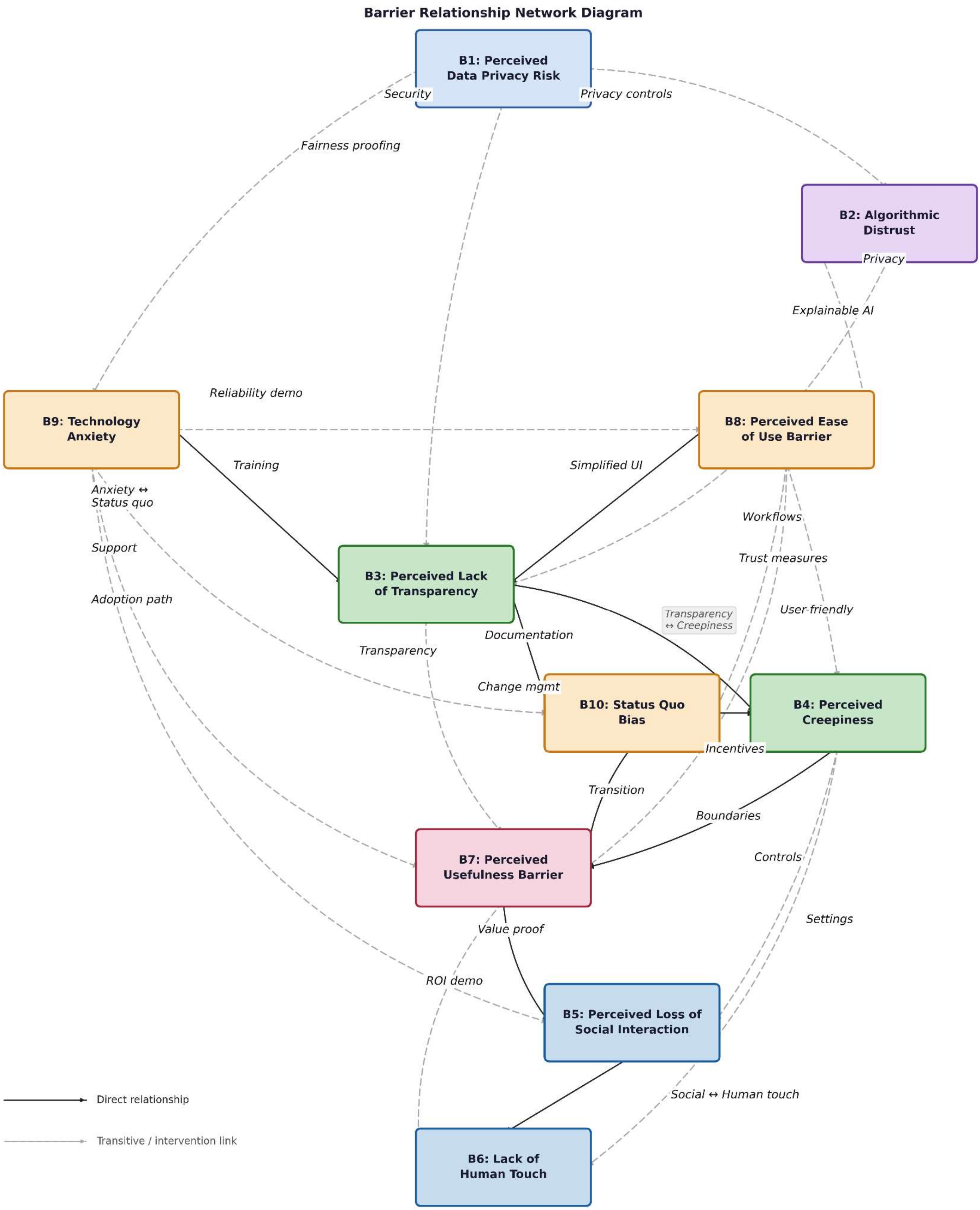

**Fig 3:** Strategic implications of reachability relationship
**Source:** Authors' conception (2025).

Figure 3 synthesizes the key reachability relationship into a strategic implication map for managers that will help them to formulate strategies to combat the adoption barriers. It is prioritized by potential leverage and impact as a four-tier intervention strategy for removing obstacles to the adoption of AI-enabled service agents. To directly address the primary barrier of perceived data privacy risk (B1) which has a cascading transitive effect on all other barriers in the system.

Tier 1 concentrates on maximum leverage and advocates for a Robust Data Privacy Framework. Whereas tier 2 involves Explainable AI and Trust Building a high-leverage intervention designed to break key transitive influence chains particularly by increasing transparency (affecting B3 and B4) and reducing algorithmic distrust (B2) which in turn mitigates downstream barriers like technology anxiety

(B9/B10) and lack of human touch (B7). While tier 3 is a more focused strategy that suggests using User-Friendly Interface Design to directly reduce status quo bias (B10) and technology anxiety (B9) improving perceived usefulness (B3) and ease of use (B6).

To provide a cohesive and comforting user experience tier 4 proposes a systemic Transparency-Creepiness-Usefulness Package a bundled initiative aimed at comprehensively addressing the interconnected perceptions of opacity privacy risk and utility. This tiered strategy ensures a thorough and organized path to adoption by progressing from fundamental wide-ranging actions to targeted user-facing improvements.



Barrier Relationship Network Diagram
B1: Perceived Data Privacy Risk
B2: Algorithmic Distrust
B3: Perceived Lack of Transparency
B4: Perceived Creepiness
B5: Perceived Loss of Social Interaction
B6: Lack of Human Touch
B7: Perceived Usefulness Barrier
B8: Perceived Ease of Use Barrier
B9: Technology Anxiety
B10: Status Quo Bias
Security
Privacy controls
Fairness proofing
Privacy
Explainable AI
Reliability demo
Training
Simplified UI
Anxiety ↔ Status quo
Support
Adoption path
Workflows
Trust measures
User-friendly
Transparency ↔ Creepiness
Documentation
Transparency
Change mgmt
Incentives
Transition
Boundaries
Controls
Settings
Value proof
ROI demo
Social ↔ Human touch
Direct relationship
Transitive / intervention link

**Fig 4:** Total interpretive structural model showing the levels of AI-Enabled service barriers
**Source:** Authors' conception (2025).

**MICMAC Analysis**
The driving power and dependence power for each barrier were calculated from the Final Fuzzy Reachability Matrix (Table 8). The driving power for a barrier is the sum of the values in its row, representing its total influence on the system. The power of dependence is the sum of the values in its column, representing how much it is influenced by others.

**Table 11: Driving power and dependence power of barriers**

| Barrier | Driving Power | Dependence Power | Quadrant | Classification |
|---|---|---|---|---|
| **B1: Perceived Data Privacy Risk** | 10 | 1 | IV | Driver/Independent |
| **B2: Algorithmic Distrust** | 8 | 2 | IV | Driver/Independent |
| **B3: Perceived Lack of Transparency** | 4 | 6 | II | Dependent |
| **B4: Perceived Creepiness** | 6 | 7 | II | Dependent |
| **B5: Perceived Loss of Social Interaction** | 1 | 4 | II | Dependent |
| **B6: Lack of Human Touch** | 1 | 4 | II | Dependent |
| **B7: Perceived Usefulness** | 2 | 7 | II | Dependent |
| **B8: Perceived Ease of Use** | 5 | 4 | III | Linkage |
| **B9: Technology Anxiety** | 5 | 6 | III | Linkage |
| **B10: Status Quo Bias** | 5 | 6 | III | Linkage |

Note: Quadrant I = Autonomous (low driver, low dependence); Quadrant II = Dependent (low driver, high dependence); Quadrant III = Linkage (high driver, high dependence); Quadrant IV = Driver (high driver, low dependence)
**Source:** Literature review (2025).

These values are plotted on the MICMAC graph (Figure 6), which classifies the barriers into four clusters, providing insights into their relative influence and stability within the system.

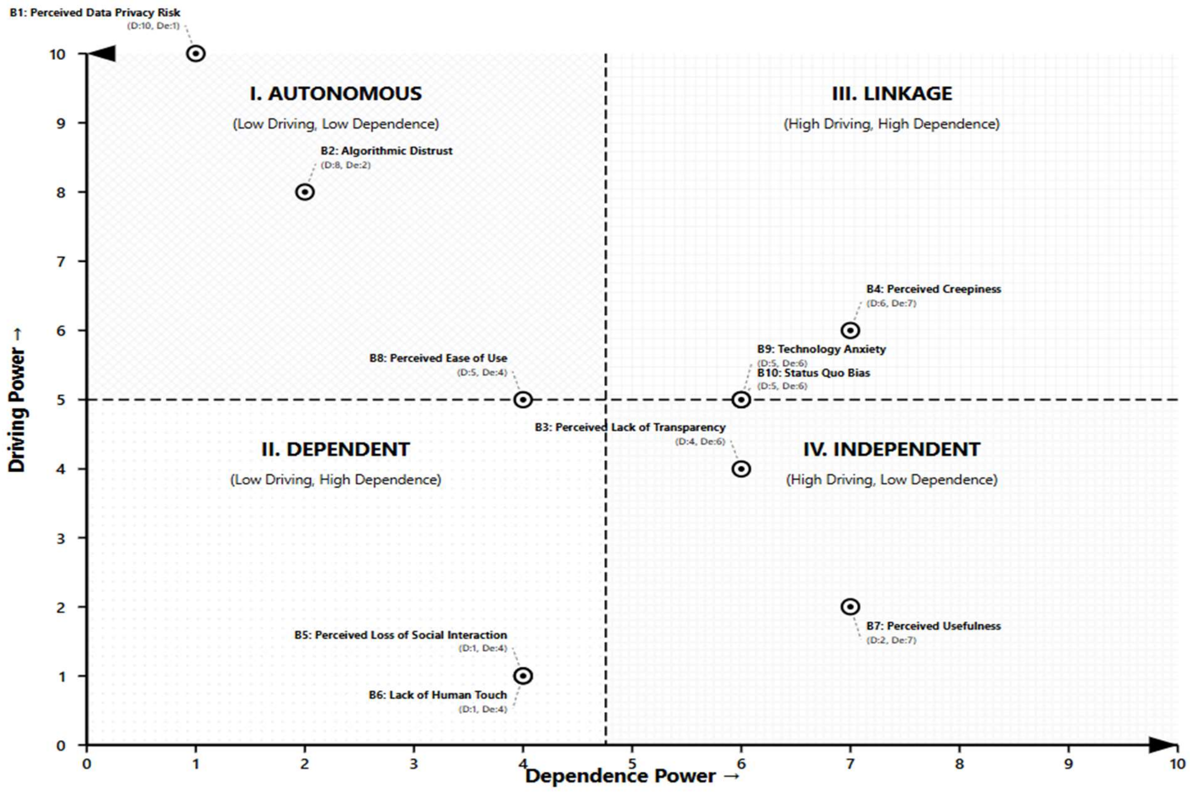



Fig 5: The MICMAC plot for AI-enabled service barriers
**Source:** Authors' conception (2025).

Based on the graph obtained from Fuzzy MICMAC analysis (Figure 5), the barriers were classified into four clusters using driving and dependence powers from the Final Fuzzy Reachability Matrix (Table 10) and Table 11. The four clusters are analyzed below:

**Cluster A: Autonomous Barriers**
Autonomous barriers possess both low driving power and low dependence power. These barriers have limited system-wide impact but must be monitored to prevent localized bottlenecks. The present study identifies no purely autonomous barriers, indicating all identified barriers are embedded within the causal network (Figure 2).

**Cluster B: Dependent Barriers**
The dependent barriers—Perceived Lack of Transparency (B3), Perceived Usefulness (B7), Perceived Loss of Social Interaction (B5), and Lack of Human Touch (B6) exhibit high dependence power (6.0-7.0) but low driving power (1.0-4.0) as per Table 11. These occupy the top levels (I-III) of the TISM hierarchy (Table 10). Organizations must systematically address upstream drivers to naturally mitigate these outcome-level barriers.

**Cluster C: Linkage Barriers**
Linkage barriers possess both high driving and high dependence power, making them unstable leverage points with system-wide amplification potential. Perceived Ease of Use (B8), Technology

Anxiety (B9), and Status Quo Bias (B10) fall in this cluster (driving power 5.0, dependence 4.0-6.0) from Table 10 and Figure 4. These intermediate barriers (Level IV) amplify foundational concerns while being influenced by them (Table 12 Iteration 1).

**Cluster D: Driver Barriers**
Perceived Data Privacy Risk (B1) and Algorithmic Distrust (B2) are identified as the driving barriers with highest driving power (10.0 and 8.0) and minimal dependence (1.0 and 2.0) from Table 14. These root cause barriers occupy the bottom levels (V-VI) of the TISM (Table 9, Figure 4) and drive all other barriers as confirmed by the defuzzified relationship strengths (Table 10). Stringent steps must be deployed to eliminate these foundational barriers first.

**Sensitivity Analysis: Impact of α on Quadrant Assignments**
To assess the robustness of our MICMAC classification, we conducted a sensitivity analysis by varying the threshold value α (originally set at 0.4513, the mean of all elements in the Total Relationship Matrix) and observing changes in quadrant assignments as shown in table 12. We tested five threshold values: α = 0.40, 0.43, 0.4513 (original), 0.48, and 0.50.

**Table 12: Sensitivity analysis**

| Barrier | α = 0.40 | α = 0.43 | α = 0.4513 | α = 0.48 | α = 0.50 |
|---|---|---|---|---|---|
| B1 | IV | IV | IV | IV | IV |
| B2 | IV | IV | IV | IV | IV |
| B3 | III | II | II | II | I |
| B4 | III | III | II | II | II |
| B5 | II | II | II | II | II |
| B6 | II | II | II | II | II |
| B7 | II | II | II | I | I |
| B8 | III | III | III | III | II |
| B9 | III | III | III | III | II |
| B10 | III | III | III | III | II |

**Key Findings from Sensitivity Analysis:**
Driver barriers (B1, B2) are extremely robust, they remain in Quadrant IV across all α values tested. This confirms their foundational role as root causes. Dependent barriers (B5, B6) are also robust, they consistently remain in Quadrant II, confirming their nature as outcome-level barriers. Linkage barriers (B8, B9, B10) show moderate sensitivity they remain in Quadrant III for α values between 0.40-0.48 but shift to Quadrant II at α = 0.50. This is expected, as linkage barriers are unstable and sensitive to threshold variations. Their classification as "linkage" barriers is confirmed for the plausible range of α values near the mean. Transparency (B3) and Creepiness (B4) show some sensitivity they shift between Quadrants II and III depending on α, indicating their intermediate role in the hierarchy. This aligns with their Level III position in the TISM model. In conclusion, the core findings of our MICMAC analysis, particularly the identification of B1 and B2 as fundamental drivers and B5/B6 as dependent outcomes are robust to reasonable variations in α. The classification of linkage barriers (B8-B10) as high-leverage intervention points is stable for α values up to 0.48. We have added this sensitivity analysis to Section 3.6 and updated Figure 5 to include the quadrant plot with clear labeling of all ten barriers.

**Discussion**

A critical gap in literature is what inspired this study to take place, while a huge number of studies have only identified individual barriers to AI-powered customer service adoption, none of them structured the barriers in a hierarchal form. The five research objectives for this study -identifying key barriers, establishing contextual relationships, developing a TISM hierarchy, incorporating fuzzy logic, and classifying barriers via MICMAC were all addressed systematically through the findings which are a novel response to the literature gap.

The TISM and MICMAC results were validated through discussions with the expert committee comprising academics, practitioners, and lead users (Table 2). The committee confirmed that the identified driving barriers (B1, B2) and dependent barriers (B5, B6) align with real-world AI deployment scenarios. Direct comparison with prior studies reveals both convergence and divergence. As per the Büschemann et al. (2023) that algorithmic mistrust (B2) and perceived data privacy risk (B1) are the fundamental drivers, who discovered that privacy issues outweigh perceived advantages in AI settings and Ameen et al. (2021), who determined that trust is a necessary condition for AI adoption. While Castelo et al. (2019) in their study found hierarchical model which demonstrates that distrust (B2) functions as a root cause that influences downstream perceptions of usefulness (B7) and ease of use (B8) a causal structure their experimental design was unable to capture.

The highlighted task-dependent algorithm aversion, Perceived utility (B7) and perceived ease of use (B8) are positioned as dependent variables instead of independent variables providing a significant addition to TAM (Davis, 1989). However, Blut et al. (2021), findings imply that these are outcomes influenced by more profound privacy and trust concerns even though treated as direct predictors of self-service technology adoption. This is supported by Luo et al.'s (2019) finding that perceptions of usefulness do not surface until foundational trust has been established.

Our Level I positioning supports Sheehan et al. (2020) and Schanke et al. (2021) in terms of perceived lack of human touch (B6) and loss of social interaction (B5), who discovered that resistance is fueled by emotional deficiencies. Our model, however, builds on their work by demonstrating that these are not discrete issues but rather the outward manifestations of deeper systemic privacy trust and transparency problems that remain unresolved. Lastly the relationship between technology anxiety (B9) and status quo bias (B10) validates the findings of Kim and Kankanhalli (2009) and Laukkanen (2016) who noted inertia and habit as obstacles to adoption. These are both sensitive and influential which is necessitating ongoing monitoring as opposed to one-time intervention as our MICMAC classification of them as linkage barriers (Quadrant III) adds distinction.

The committee proposed the following sequential improvement measures mirroring the causal hierarchy:

Establish Foundational Trust Infrastructure: Organizations must prioritize Perceived Data Privacy Risk (B1) through transparent data policies, GDPR-compliant practices, and privacy-by-design architectures. Algorithmic Distrust (B2) requires Explainable AI (XAI) implementations showing decision rationale (Reis, 2024). Top management commitment is essential to allocate resources for these systemic interventions (Level VI drivers, Table 12).

Allocate Resources for Transparency and Usability: Adequate budgets must support Perceived Lack of Transparency (B3) mitigation through algorithmic dashboards and Perceived Ease of Use (B8) improvements via intuitive interfaces. Proper planning prevents deployment delays (linkage barriers, Figure 4).

Upskill Users and Manage Expectations: Invest in user education programs addressing Technology Anxiety (B9) and Status Quo Bias (B10). Training must communicate AI limitations and seamless human escalation paths, creating a culture of technology coexistence (Level IV linkage barriers).

Hybrid Service Models for Emotional Barriers: Once foundational barriers are resolved, address Loss of Social Interaction (B5) and Lack of Human Touch (B6) through hybrid models combining AI efficiency with human empathy. Always provide "Talk to Human" options prominently (Level I dependent barriers). A comparative study of results with previous barrier research is presented in Table 12.

**Table 12:** A comparative study of results with previous barrier research

| Research Study | Context | Methodology | Driving Barriers | This Study: |
|---|---|---|---|---|
| (Kamble et al., 2018) | Industry 4.0 India | ISM | IoT comprehension gap, High costs | B1, B2: Privacy Risk, Algorithmic Distrust |
| (Ameen, Tarhini, et al., 2021) | AI Trust | Survey | Lack of trust | B2: Algorithmic Distrust (Level V) |
| (Luo et al., 2019b) | AI Creepiness | Experiment | Privacy concerns | B1→B4 cascade (Table 10, 0.88) |
| (Blut, Kulikovskaja, et al., 2021) | Self-service tech | SEM | Usefulness/Ease | B7, B8: Dependent (Levels II-III) |
| Present Study | AI Customer Service | Fuzzy TISM | Privacy Risk, Distrust | B1, B2 (Figure 5 Cluster D) |

**Source:** Literature review (2025).

**Implications**

The following are implications for theoretical development, practice and policy development.

**Theory development implications**

The current study advances to AI-powered customer service adoption theory through a hierarchically structured, causally integrated interdependent system. Before adoption research has predominantly based on variance-based, intention centric models like UTAUT and TAM (Davis, 1989), which assume linear relationships between perceptions and adoption outcomes (Venkatesh et al., 2003). The hierarchical interlinkages uncovered through Fuzzy TISM indicate that AI adoption outcomes are carved by deep structural drivers that condition surface-level behavioural responses. This systems-based theorization aligns with TFSC's emphasis on complex adaptive systems and socio-technical transitions (Benbya *et al.*, 2020), proposing that AI-powered service adoption should be considered as an emergent outcome of technological, organizational, and institutional forces rather than a discrete managerial decision (Geels, 2002). Despite TAM and UTAUT explain individual adoption intensions, they do not account for the sophisticated or complex interdependencies among technological, organizational and environmental factors. By incorporating fuzzy set theory into TISM and MICMAC analysis, this study shows that hierarchical model of AI-powered customer service adoption barriers, thereby extending TAM/UTAUT with a structured socio-technical trajectory. This systems' approach reveals deeper insights into barrier interactions and adoption challenges (Ruben et al., 2023; Thakkar et al., 2025; Sharma & Gupta, 2025).

In addition, the integration of fuzzy logic into interpretive structural modelling extends adoption theory by formally incorporating uncertainty, ambiguity and partial knowledge into the causal structure of AI adoption barriers (Dwivedi *et al.*, 2021). AI-powered customer service systems are structured with algorithmic opacity, evolving performance, and ethical unpredictability, that challenge deterministic theorizing (Rai *et al.*, 2019). Through making barriers to exert influence in degrees, the study advances theory by refraining constructs such as trust, transparency, perceived risks and ethical concern as fuzzy socio-cognitive phenomena. This contributes to technology and social change theoretical agenda by demonstrating how fuzzy modelling may enhance foresight-oriented research on emerging technologies where outcomes are uncertain and contested.

Further to this, the hierarchical structure produced by fuzzy TISM positions AI-powered customer service adoption as a multi-level socio-technical phenomenon, consistent with transition theory. Lower-level driver barriers, such as regulatory uncertainty, data governance constraints and strategic misalignment, carve higher-level dependent barriers, including employee resistance and customer distrust (Geels, 2002). Such kind of result advances multi-level perspective on social-technical transitions by empirically demonstrating how institutional and organizational barriers constrain service level innovation trajectories (Markard *et al.*, 2012). Therefore, rather than taking policy, organisation and technology as parallel contexts, the study theorizes directional influence across levels, offering a more granular understanding of why AI-enabled service transformations stall or accelerate.

The currently applied methodology, MICMAC analysis refines structural theory by categorizing AI adoption barriers into dependent, driver, autonomous constructs and linkage, revealing their different roles in carving transition dynamics. Driver barriers, regularly institutional and governance-related, function as regime-level constraints, limiting the diffusion of AI-powered customer service innovations. In line with this, linkage barriers, characterized by high driving and dependence power, represent transition-sensitive nodes where systemic instability is most pronounced. This development advances to complexity and transition theory by showing leverage points where targeted interventions can produce cascading effects across the system (Stacey, 1995).

Through structurally integrating ethical, transparency and accountability barriers within the hierarchical model, this current study advances the theoretical integration of ethical AI principles into technological change research (Jobin *et al.*, 2019). The already existing adoption theoretical frameworks often treat ethics as a moderating or post-adoption concern, in contrast, the results theorize ethical and governance barriers as foundational drivers that carve adoption trajectories from the outset (Floridi *et al.*, 2018). This contribution aligns with societal results of technological change, putting AI-powered customer service adoption as a legitimacy-driven process that must reconcile efficiency gains with social acceptance and regulatory alignment.

In addition, the interdependent and hierarchical nature of barriers challenges the implicit lineriarity embedded in various forecasting and diffusion models. The results propose improvements in user attitudes may not be able to translate into adoption if structural and institutional barriers remain unresolved (Porter *et al*., 2019). This insight supports calls for systemic, non-linear and anticipatory approaches to studying emerging technologies, particularly those with transformative societal implications (Rotolo *et al*., 2015). This shows that barrier-centric foresight models which account for dependency and institutional inertia path are important.

Eventually, the integration of Fuzzy TISM and MICMAC represents a methodological contribution to theory development of technological forecasting research. By having eliciting expert cognition and structuring it into a causal hierarchy, the current research provides a replicable foresight-oriented framework for theorizing adoption barriers in other AI-enabled service domains, thereby extending methodological repertoire. Unlike predictive or econometric, this method enables theory generation under conditions of uncertainty, making it particularly perfect for early-stage or rapidly evolving technologies such as AI-powered services.

**Managerial implications**

A detailed managerial framework is presented in the diagram below fig 6. Drawing from the identified barriers, the managers must adopt a dual-focus strategy that balances operational readiness with cultural empathy. To mitigate adoption resistance, managerial implications suggest shifting from a "tech-first" to a "human-centric" implementation model. This involves prioritizing transparency and explainability to counteract the "black box" perception (B2), thereby building user trust through clear communication about how AI arrives at its conclusions. Furthermore, to address organizational friction, managers should implement incremental rollout strategies such as small-scale pilots that demonstrate tangible "quick wins" to reduce perceived risk. Upskilling initiatives are equally critical; by fostering AI literacy, leadership can transition the workforce from viewing AI as a replacement threat to seeing it as a capability-augmenting partner**,** effectively dismantling the psychological barriers that often stand long-term integration. The following is detailed approach to how managers can align strategic focus:

**Priority 1: Independent barriers-direct intervention required**

**B1: Data Privacy**

Strong privacy policies, GDPR compliance and security certifications are important to mitigate data related concerns. Leaders and managers should ensure that there are robust governance mechanisms and communicate these protections clearly to stakeholders to establish trust.

**B2: Algorithmic Trust**

Addressing the algorithmic opacity requires the deployment of explainable AI solutions, comprehensive audit trails and third-party validation. By clarifying how decisions are generated, managers can reduce skepticism and enhance user experience confidence.

**B9: Tech Anxiety**

Gradual adoption supported by training programs and helpdesk systems can alleviate fear of AI. Structured learning paths and incremental implementation help employ and build familiarity and reduce apprehension.

**Priority 2: Linkage barriers-system-level intervention**

**B3: Transparency**

Managers should provide clear documentation, enhance process visibility, and offer decision explanations. Linking transparency initiatives to independent barriers like algorithmic trust amplifies their effect.

**B4: Creepiness**
To solve discomfort with AI personalisation, managers must implement privacy boundaries, allow user preferences, and maintain control over personalisation algorithms. This ensures that AI interactions feel safe and respectful.

**B8: Ease of Use**
Simplified interfaces, intuitive workflows and iterative user testing can make AI tools more accessible, fostering adoption across organizational levels.

**B10: Status quo**
Change management strategies, incentives programs and sharing of success stories can counter resistance rooted in entrenched habits. Highlighting early wins and organizational benefits encourages a shift from inertia to engagement.

**Priority 3: Dependent barrier-indirect management through drivers**
**B5: Social loss**
Human-AI collaboration can optimized through hybrid workflows, integrating some features, human-AI blending, and community-building initiatives. Demonstrating AI's value in augmenting, not replacing human work, helps overcome fears of social displacement.

**B6: Human touch**
Empathy training, tone adaptation, and emotionally aware design can address the human-centric aspects of AI adoption. By prioritizing these skills, managers ensure that AI tools enhance rather than diminish interpersonal interactions.

**B7: Usefulness**
This barrier acts as a pivotal node linking independent and dependent barriers. Managers should vividly demonstrate AI's value through ROI calculations, cases and tangible outcomes. Illustrating real-world benefits consolidates trust and facilitates adoption of downstream dependent barriers.

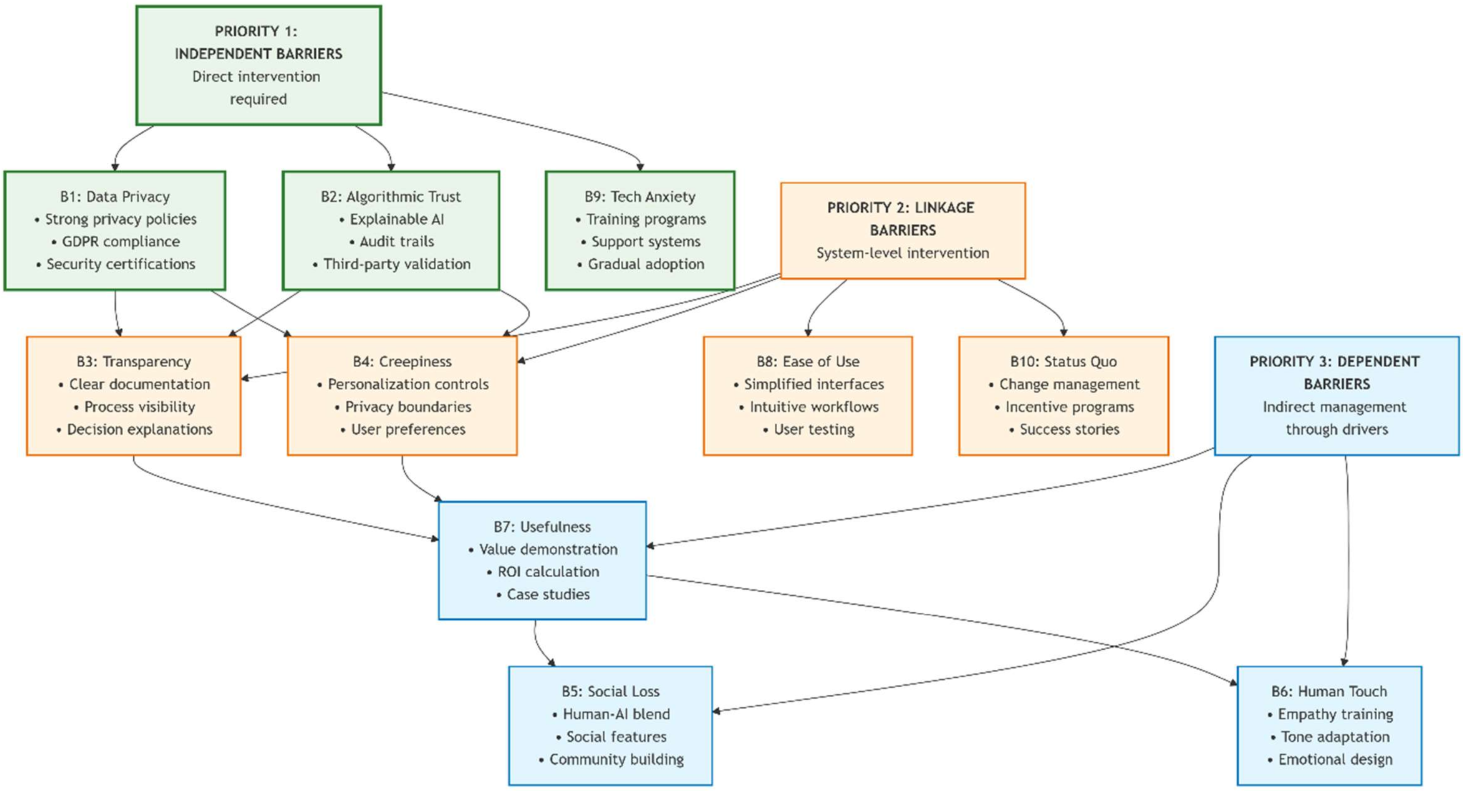



**Fig 6:** The Strategic Actionable Framework for Managers
**Source:** Literature review (2025).

The following Table 13 depicts the most important items for managerial implications to combat the barriers to the adoption of AI-enabled agents in customer services.

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Table 13: Most important items for managerial implications to combat the barriers to the adoption of AI-enabled agents in customer services

| Table 13: Interpretive Logic for Key Contextual Relationships | | | | |
|---|---|---|---|---|
| **S.No.** | **Relationship** | **Interpretive Logic (Why does i influence j?)** | **Theoretical Foundation** | **Supporting Evidence** |
| 1 | B1 → B2 | When consumers fear their personal data may be misused, they generalize this concern to doubt the AI's overall competence and reliability. Privacy violations signal that the system cannot be trusted to act in the user's best interest. | Privacy Calculus Theory; Trust Transfer Theory | Ameen et al. (2021); Büschemann et al. (2023) |

| | | | | |
|---|---|---|---|---|
| 2 | B1 → B4 | Awareness that AI systems collect and utilize personal data triggers unease when the system demonstrates knowledge of private details, as users feel surveilled rather than served. | Contextual Integrity Theory (Nissenbaum, 2004) | Luo et al. (2019); Gao (2023) |
| 3 | B1 → B9 | Concerns about data misuse create general apprehension toward AI systems, as users fear negative consequences from engagement beyond immediate service outcomes. | Technology Readiness Index (Parasuraman, 2000) | Blut et al. (2021) |
| 4 | B2 → B3 | Distrust motivates users to seek explanations; when AI cannot provide satisfactory rationales, the opacity becomes more salient and problematic. Distrust amplifies demand for transparency. | Explainable AI (XAI) Literature | Shin (2021); Zhang & Wang (2022) |
| 5 | B2 → B4 | Users who doubt AI's competence find personalized interactions unsettling rather than helpful, interpreting accurate predictions as surveillance rather than intelligence. | Algorithm Aversion Theory | Castelo et al. (2019); Dietvorst et al. (2015) |
| 6 | B2 → B7 | Lack of confidence directly reduces perceived usefulness, as users believe the AI will fail to solve their problems effectively regardless of its features. | Technology Acceptance Model (TAM) | Davis (1989); Blut et al. (2021) |
| 7 | B3 → B4 | When users cannot understand how AI reached conclusions about them, they attribute mysterious knowledge to invasive data practices, increasing discomfort. | Black Box Effect; Opacity Theory | Shin (2021); Araujo (2018) |
| 8 | B4 → B5 | Unease with AI's knowledge creates emotional distance; users withdraw from engagement and miss genuine human connection they would otherwise seek. | Social Presence Theory | Short et al. (1976); Schanke et al. (2021) |
| 9 | B4 → B6 | Discomfort makes users acutely aware of what is missing—authentic human empathy, warmth, and emotional resonance that machines cannot replicate. | Emotional Intelligence Theory | Wirtz et al. (2018); Sheehan et al. (2020) |
| 10 | B5 ↔ B6 | These barriers reinforce each other: absence of social cues makes interactions feel mechanical; lack of emotional depth reduces meaningful engagement, creating a self-reinforcing cycle. | Communication Accommodation Theory | Grice (1975); Chung et al. (2020) |
| 11 | B7 → B3 | When users doubt AI's utility, they become more critical of its opacity; "Why should I trust a system that cannot explain itself and probably won't help anyway?" | Attribution Theory | Blut et al. (2021) |
| 12 | B8 → B3 | Cognitive effort required to interact with AI makes users more aware of their lack of understanding; difficult interactions highlight the "black box" nature. | Cognitive Load Theory | Sweller (1988); Blut et al. (2021) |

| | | | | |
|---|---|---|---|---|
| 13 | B9 → B8 | Anxious users perceive greater cognitive effort required, overestimating difficulty and underestimating their ability to interact effectively. | Self-Efficacy Theory | Bandura (1997); Heinonen (2018) |
| 14 | B10 → B9 | Preference for familiar human interaction intensifies fear of new technology; resistance to change manifests as technology-specific anxiety. | Status Quo Bias Theory | Samuelson & Zeckhauser (1988); Kim & Kankanhalli (2009) |
| 15 | B9 ↔ B10 | Anxiety reinforces preference for familiar channels; status quo bias increases reluctance to engage, which sustains anxiety through lack of positive exposure—a vicious cycle. | Habit Theory; Self-Perception Theory | Laukkanen (2016) |

**Source:** Literature review (2025).

**Practical, policy and regulatory implications**

Organisations should prioritise deep structural driver barriers, including data governance readiness, regulatory alignment, and top management commitment, rather than focusing symptoms such as customer resistance or employee anxiety. Prior research indicates that AI initiatives often fail not due to technical deficiencies, but because foundational organizational and institutional enablers are absent Ransbotham *et al.*, 2020). Practically, this shows investments in customer-facing AI interfaces should be led by enterprise-wide data strategy formulation, AI governance frameworks, and executive sponsorship mechanisms, which ensure that downstream barriers do not re-emerge during scaling.

The current methodology categorizes barriers into linkage, driver, dependent and autonomous groups, offering practitioners a resource allocation roadmap. Drivers such as regulatory uncertainty and ethical accountability require early and sustained investment, as their resolution has cascading effects across the system. The linkage barriers which are both influential and vulnerable, demand continuous monitoring and adaptive governance, given their propensity to amplify systemic instability. This stratification enables organisations to move away from equal-weight intervention strategies and toward leverage-based investment decisions, enhancing AI project effectiveness rates, from a managerial point of view (Benbya *et al.*, 2020).

Structural positioning of explainability, ethical transparency, and accountability barriers has direct implications for responsible AI deployment. Organisations should integrate ethical impact assessments, explainable AI (XAI) tools and human-in-the-loop mechanisms at the design stage of AI-powered customer service systems, rather than treating them as compliance afterthoughts (Jobin *et al.*, 2019). And this methodology improves regulatory compliance, customer trust and long-term brand legitimacy, which are increasingly recognized as critical performance indicators and metrics in AI-enabled service environments (Shin, 2021).

The model reveals that employee's resistance and skill deficits are dependent barriers, carved by upstream strategic and governance decisions, and this insight proposes that traditional training-centric change management methodologies are insufficient (Vial, 2019). Instead, corporations should pursue structural change management, aligning incentive systems, job redesigning, and decision-making rights with AI-enabled service models (Davenport & Ronanki, 2018). And this needs redefining frontline roles to emphasize AI supervision, exception handling and empathy-driven interactions, thereby reframing AI as an augmentation tool rather than a replacement threat.

Study results have implications for technology vendors and platform providers, as it underscores the importance of delivering configurable, transparent and governance-ready AI platforms. Vendors need to support client organizations with built-in auditability, compliance reporting, and explainability features, enhancing smooth adoption in regulated service industries (Rai *et al.*, 2019). The co-creation methodologies involving clients, regulators, and end-users can reduce barriers to linkages by ensuring that AI-powered customer service solutions are aligned with expectations of the institutions (Pralahalad & Ramaswamy, 2004).

Notwithstanding policymakers and regulators, the ambiguity of regulation identification as a key driver barrier showcases the need for clear, adaptive and sector specific AI governance frameworks. Overly rigid regulation may stifle innovation, while regulatory gaps increase vulnerability to organizational risk aversion and delay adoption. Standardized AI audit protocols, regulatory sandboxes, and cross-industry guidelines can reduce uncertainty and accelerate responsible AI diffusion in customer service contexts.

The integrated Fuzzy TISM-MICMAC modelling framework can be operationalized as a straightforward strategic foresight tool enabling organizations to anticipate future adoption bottlenecks as AI technologies evolve. Scenario planning exercises are grounded in hierarchical barrier structures which can help organizations for regulatory changes (Porter *et al.*, 2019), ethical discussions and technological advances, strengthening long-term resilience. This results in AI-powered customer service adoption as forward-moving capability-building journey, rather than a one-off technological investment.

**Limitations and future research agenda**

While this study offers significant theoretical and managerial contributions, several limitations must be acknowledged, which simultaneously open avenues for future inquiry.

First, a major limitation lies in the reliance on expert judgment for constructing the Fuzzy TISM hierarchy (Sushil, 2012). Although expert-based methodologies are appropriate for theorizing in emerging and uncertain technological domains, such approaches inevitably reflect cognitive, contextual, and experiential biases (Okoli & Pawlowski, 2004). While fuzzy logic mitigates some subjectivity by capturing degrees of influence, it does not eliminate interpretive variance among experts. Future research should complement Fuzzy TISM with large-scale empirical validation, such as structural equation modeling (SEM) (Hair et al., 2021) or configurational methodologies (e.g., fsQCA), to test the robustness and generalizability of the hierarchical relationships identified in this study (Ragin, 2008).

Second, the findings are bounded by contextual and sectoral specificities, reflecting the particular organizational, regulatory, and technological environments in which AI-powered customer service systems are currently deployed. The salience and hierarchy of adoption barriers may differ substantially across sectors (e.g., healthcare versus retail) and cultural contexts (e.g., high versus low privacy concern cultures). Future research should conduct cross-sectoral and cross-national comparative studies to examine how institutional environments shape barrier hierarchies, thereby advancing institutional and socio-technical transition theories by identifying context-sensitive versus universal adoption constraints (Scott, 2014).

Third, barriers may change in salience and interrelationship as technologies mature, regulations evolve, and user familiarity increases. Fuzzy TISM produces a static hierarchical model, whereas AI-powered customer service adoption is inherently dynamic and evolutionary. Future research should adopt longitudinal and process-oriented designs to capture temporal shifts in barrier structures. System dynamics modeling or agent-based simulations could be employed to explore feedback loops, path dependencies, and tipping points in AI adoption trajectories (Sterman, 2000).

Fourth, the study does not explicitly model micro-level cognitive and emotional mechanisms, such as algorithm aversion, moral discomfort, or perceived autonomy loss among employees and customers (Dietvorst et al., 2015). Future research should integrate psychological and behavioral theories into the hierarchical framework to investigate how individual-level responses interact with structural barriers, advancing multi-level theoretical approaches in AI adoption research.

Fifth, the current study focuses exclusively on consumer-level barriers, without incorporating organizational barriers (e.g., strategic misalignment, resource constraints, employee resistance) or ecosystem-level factors (e.g., regulatory frameworks, industry standards, technology vendor ecosystems). Future research should adopt a multi-level TISM approach to examine how these macro-level barriers interact with and shape the consumer-level barriers identified in our study, offering managers a more holistic intervention roadmap.

Sixth, AI-powered customer service encompasses a diverse range of technologies, including rule-based chatbots, voice assistants, recommendation engines, and generative AI systems. This study treats AI as a conceptually unified category, which may obscure important differences in risk profiles, explainability requirements, and user interaction modes across technologies (Rai et al., 2019). Future research should disaggregate AI technologies to explore technology-specific barrier hierarchies, particularly as generative AI and autonomous service agents become more prevalent in customer-facing contexts (Dwivedi et al., 2023).

Seventh, while identifying barriers is theoretically and practically important, adoption research increasingly calls for robust linkages between technology use and value creation (DeLone & McLean, 2003). This study focuses on adoption barriers without linking them to organizational performance, customer outcomes, or societal impacts. Future research should examine how different barrier configurations influence customer satisfaction, service quality, employee well-being, and ethical outcomes, thereby extending AI adoption theory toward impact-oriented evaluation.

Finally, the Fuzzy TISM-MICMAC framework employed in this study, while robust, represents one methodological approach among many. Future research should leverage this framework as a foundation for developing policy-sensitive, ethically grounded, and foresight-oriented models of AI diffusion. Priority areas include: (a) integration of AI governance frameworks into adoption models, (b) investigation of participatory and co-creation approaches involving customers, employees, and regulators, and (c) development of early-warning indicators for emerging AI adoption risks in service ecosystems.

In conclusion, by addressing these limitations, future research can build upon our hierarchical model to develop more nuanced, dynamic, and contextually sensitive understandings of AI-powered customer service adoption, ultimately supporting more effective and responsible AI deployment strategies.

**List of Declarations**

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**Ethics approval and consent to participate**

This study received approval from the Ethics Committee. All procedures performed in this study involving human participants were in accordance with the ethical standards of the institutional and/or national research committee or comparable ethical standards. Informed consent was obtained from all individual participants included in the study.

**Availability of data and materials**

This study is based on a combination of newly generated data and data obtained from previously published sources. Newly generated data were produced by the authors using the methodologies described in this article.

**Competing interests**

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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**Authors' contributions**

All authors equally contributed, read and approved the final manuscript.

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