IRJEMS International Research Journal of Economics and Management Studies
ISSN: 2583 – 5238 / Volume 5 Issue 4 April 2026 / Pg. No: 94-109
Paper Id: IRJEMS-V5I4P113, Doi: 10.56472/25835238/IRJEMS-V5I4P113

Original Article

Limits of Automation in Contact Centers: Analyzing Customer Inquiries beyond the Capabilities of AI

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Received Date: 10 March 2026 Revised Date: 30 March 2026 Accepted Date: 06 April 2026 Published Date: 15 April 2026

Abstract: *The advent of artificial intelligence implemented at contact centers and its fast increase in usage has transformed customer service by allowing for a widespread automation of the huge quantity of interactions occurring in an operation, but the limits of this automation are still not well defined, particularly when dealing with complex customer queries. We investigate the extent to which inquiry difficulty affects the probability of escalation from AI agents to human assistants in contact center settings. The analysis is from a dataset of 9,177 customer touchpoints from an AI-enabled telecommunications contact centre for 4 months (September–December 2025). The results indicated, through descriptive and binary logistic regression, a strong, statistically relevant relationship between the complexity of the inquiry and the rate of escalation, with 5.3% in the low complexity setting increasing to 87.0% in the high level. The regression outcomes further reveal that for each 1-unit increase in complexity, the probability of escalation increases by about 72.6%, illustrating a strong effect size. These findings reflect the fact that, although AI systems deliver very well when used for typical and specific inquiries, they do remarkably poorly in complex, ambiguous and multi-issue encounters. By discovering that inquiry complexity is a critical factor in the operational limits of AI-based automation, the study adds to the literature and provides insights on how organizations can mitigate these to drive both operational efficiency and service experience with hybrid service models and complexity-based routing strategies.*

Keywords: *Automation, Contact Centers, Customer Inquiries, Ai Agents, Escalation, Chatbots, Voicebots, Inquiry Complexity.*

I. INTRODUCTION

The fast pace of deployment of artificial intelligence technologies has revolutionized customer service in organizations (Inavolu, 2024). In the past few years, contact centres have been adopting AI-based automation solutions (voicebots and chatbots) in response to high volume of consumer enquiries through the use of such (Hibban, 2025). Such systems are able to infer customer intent, standardize, and solve problems autonomously. This allows organizations to cut down on operational costs, make processes more efficient and maintain a steady stream of services. Consequently, instead of being supplementary, the use of AI agents has become integrated into the core of contemporary contact centre operations (Doellgast et al., 2023).

However, fully automated customer service is far from an assured feat. AI agents can handle routine but well-structured inquiries, however, a substantial proportion of customer interactions require transfer to human representatives (Uzoka et al., 2024). These transfers, also known as escalations, happen when AI agents do not effectively resolve customer issues. From a corporate viewpoint, escalations add time and money to handling, while from a customer perspective, they may create frustration or dissatisfaction. This raises an important tension in automated contact centres with the use of AI-based automation (although it does help with efficiency) does not automatically eliminate the need for human involvement (Rangu, 2025).

Service AI has been evaluated mainly through the lenses of technical performance, customer satisfaction level, and adoption outcomes. More specifically, less was studied when AI agents were unable to address customer questions (Noor et al., 2022). In most instances, automation is approached as a simple binary proposition, with interactions either passed down via successful AI or human agents. Overlooking the nature of the questions provides only a rudimentary understanding of why certain interactions are beyond what is possible by the AI technology (Olabiyi et al., 2025). Consequently, there is still much to be learnt about the boundaries of effective automation in contact centres.

There is, however, one key factor which might underlie such limitations, that is inquiry complexity. Inquiry complexity means the level to which a customer request is ambiguous, covers more than one problem or has a context dependency or non-routine problem solving. AI agents are generally engineered for these standardized and predictable interactions built up of predefined rules, training data, and intent recognition models (Ferraro et al., 2024).

As inquiries grow ever more complex, these systems may fail to appropriately interpret the customer's need, or to offer a relevant response. As a result, the level of complexity may be key in whether an interaction is in the hands of an AI agent or one in which a human representative is called in.

As the complexity of the inquiry increases, it is reasonable to assume that the risk for escalation will also increase. For example, a challenging question may involve flexible reasoning, context or emotional intelligence, and, in the context of a complex inquiry, contextual understanding or emotional sensitivity that would hardly ever be able to be replicable in a typical AI agent. When these problems arise, the transfer of the encounter to a human becomes an appropriate approach for optimal resolution and ongoing service improvement (Xu et al., 2020). Crucially, such transfers are not random happenstance and are in fact inextricably connected to the type of enquiry from the customer. This relationship is relevant for understanding functional boundaries of AI-based automation in contact centres (Rana et al., 2024). In this study we sought to fill these gaps by exploring the types of customer queries not suited for efficient management by AI agents and hence which need to be turned over to human representatives.

It also explores how the complexity of inquiries mediates the association between AI-enabled automation and escalation. By analyzing how automation level and inquiry characteristics interact with transfer outcomes, this research paper contributes to a better understanding of when and why AI agents are at their limits in automated contact centre environments. The thesis also adds to a more nuanced understanding of automation in customer service by examining customer interactions in an AI-enabled contact centre. Instead of examining the efficacy of AI as whether or not it can be successful, emphasis upon inquiry complexity as an important driver of service success. In the process, this paper provides insights applicable to the research as well as the practitioners as they strive to design more effective and realistic AI-assisted service systems.

II. THEORETICAL BACKGROUND AND LITERATURE REVIEW

A) AI-Based Automation in Contact Centers

Artificial intelligence technologies have revolutionized the way organizations operate contact centre systems, redefining how they handle routine inquiries from customers. Contact centres had traditionally depended on employees that were almost entirely human to fulfil inquiries from customers, leading to labour costs, limited availability of service and high variability in service quality (Inavolu, 2024).

Automation due to computer systems and the advent of AI have reduced the operational complexity of managing high volumes of standardized interactions by automating tasks such as chatbots, voicebots, virtual assistants, etc. At this time, contact centres needed to respond to customer queries but needed a trained or experienced human agent (Hibban, 2025).

Routine customer inquiries are commonly straightforward and often follow the same protocol, predictable, and structured requests, where pre-defined process or standardizations are used to resolve the question. Some other examples are checking account balance, checking order status, updating one's personal details, changing password or information about services (Ledro et al., 2025). They are low ambivalence (low context dependence) and can be expressed in terms of expected responses. They are, therefore, ideal for automation with AI-based systems that leverage intent recognition, natural language processing, and scripted generation of responses (Okeke & Akinbolajo, 2023).

Empirical evidence indicates that routine enquiries represent a significant proportion of contact centre visits. According to industry reports, 60%-80% of customer service enquiries are repetitive and rule-based, which can easily be automated (Zhao & Wu, 2025). AI-enabled intelligent agents that monitor those types of interactions allow organizations to realize significant operational efficiencies. Automation, for example, can process thousands of interactions at once, without human personnel scheduling barriers (e.g. customer wait times) and enhances access to services. AI-supported automation in routine inquiry processing can serve as one of the most attractive factors (Akinnagbe, 2024). Contact centres are the main operational expense of many organisations, where labour payments form a large percentage of overall service costs. According to estimates, AI automation can cut customer service costs by up to 30%, depending on the level of implementation and the characteristics of the service processes (Khneyzer et al., 2024). Automated systems remove the need for human intervention in simple interactions, enabling organizations to redeploy human capital into more complicated or value-add activities.

Apart from cost effectiveness, AI agents improve service consistency and accuracy in general inquiry resolution. Human agents may offer different performance because of experience, training, or workload pressure (Rawanda, 2026). On the other hand, AI systems, according to programmed rules and trained models, give standardized responses while decreasing the potential risk of informational errors in high volume queries. In addition, automated systems can work 24 hours a day giving, 7 times a week and in many international markets - especially in larger markets where consumers can ask for help anytime as they wish at no business hours (Vunnava, 2025).

The time taken on average for routine inquiries is another quantified advantage of AI automation in the response of AI in answering routine enquiries is decreased average handling time. Typical requests are easier to handle when they involve small decisions that generally are decision makers, and can generally be resolved via rapid access to data (information access or automated review) (Shahbandi, 2025). Research has indicated that AI agents can conduct basic customer interactions up to 40% quicker than human agents, leading to enhanced operational efficiency and increased transaction reach in contact centres (Mariani et al., 2023). And given AI systems have built-in capabilities to instantly tap into big databases which can help create a quick response, this can add a perceived level of service quality to a client's perceived service quality.

There is also automation in peak demand management. Invitees to the Contact centre are often affected through seasonal changes, promotional advertising and unanticipated interferences in service (Ledro et al., 2025). AI systems can help scale with the fact that they can contain a sudden spike in routine inquiries by not demanding employees on site or on call. For instance, in case of promotion or service downtimes, automated agents can handle volume information requests, minimising system congestion and preventing customer abandonment rates (Zahidi et al., 2024). Nonetheless, the success of AI automation in routine inquiries is based on the extent to which intent recognition and system training are correct. For example, automatically implemented agents depend on historical interactions data as well as a pre-defined set of user knowledge bases in order to help with interpreting customer requests (Singh, 2025).

Once the inquiries adopt familiar patterns, AI systems can successfully guide customers through fixed resolution paths. This results in lower performance in the case of an automated system if customers do not follow expected linguistic patterns or offer several problem behaviours in one interaction (Xu et al., 2020). This emphasizes the need to identify routine and non-routine inquiries when discussing the procedural limits of automation. And, beyond asking open questions, AI automation serves to handle conversation management. In many contact centre settings, AI agents are the first point of contact, they perform initial filtering, go around to see what the customer needs, sort questions and so forth before deciding whether automated response is feasible (Tirulo et al., 2026). This "triaging" function makes routing that much more efficient and avoids overworking other sales agents where their only work is to handle complex tasks or interpersonal situations.

B) Customer Inquiry Handling in Contact Centers

Customer inquiry handling is one of the key activities of the contact centre, and it affects the overall quality and customer experience. Contact centres are centralized systems that receive, process and solve customer requests through various forms of communication such as telephone, live chat, email, social media and mobile apps (Doellgast et al., 2023). How efficiently the customer inquiry is managed is directly related to customer satisfaction as well as operational efficiency, service cost, and retention of customers.

Customer inquiries are generally defined as customer-specific interactions initiated by customers to ask questions, obtain information, request help, solve problems, or complete a service transaction (Heinonen & Nicholls, 2022). These interactions are very different in terms of number of them, as well as the complexity of the interaction or how fast they are, the high level of emotion, and the problem solving effort required to have the solution. As a result, contact centres have developed structured processes in place to respond to inquiries on how they will be handled so that the timely and consistent handling of the queries generated by customers is taken care of in a systematic way (Gao et al., 2025).

These processes usually consist of steps like inquiry receiving, category and allocation, resolution and closure. A very basic process in inquiry handling is the taking of orders from customers. In standard contact centres, the latter was conducted with human assistance who returned calls or responses to written correspondence (Kocaoğlu & Acar, 2016). Yet, with a rapid uptake of digital communication technologies, the modern contact centres must process an enormous number of requests across multiple channels with limited time. Industry estimates indicate there are tens of thousands of interactions per day in large contact centres whilst peak times put significant pressure on the service (Saberi et al., 2017). As a result, structured inquiry-handling systems and standardized workflows have come to play an important role in stabilizing operations.

Customers make inquiries by way of classification or categorization after receiving. Classification is defined as the identification of the type of inquiry that needs to be solved (e.g., billing, technical support, product information requests, account management or complaint handling). Effective classification enables contact centres to assign requests to service channels or specialized teams (Chen et al., 2022). Most businesses use a mechanism called inquiry classification as an aid to search queries, where they are directed to a known answer as keywords, length of a conversation, or past customer history and the process is automated for better resolution path.

It has been proven that with accurate classification average handling time is reduced by 10–20%, on average, because it avoids unneeded transfers and ensures issues are routed to agents who need handling (Yulianto et al., 2025). Routing (which is the second key step) is in the inquiry-handling process. Upon classification, inquiries are either sent as directed to automated systems or human agents, depending on their complexity and need. Standardized and routine inquiries can be routed to AI-based service systems, while more complex or sensitive interactions pass to human representatives (Sapkota et al., 2026). For optimal contact centre performance efficient routing modes have to be established because, when misrouted, the inquiry can extend time taken to resolve it, increase operational expenses and reduce customer satisfaction. Empirical study by Stanley et al., (2022) show that up to 25% of customer frustration in contact centres is linked to redundant transfers or routing, reinforcing the criticality of making such decisions early on.

The resolution phase is the core of customer service in dealing with customer questions. At this stage, the service provider tries to meet the customer's desire by supplying information, taking account actions, solving technical problems, or offering a reward if possible (Akinnagbe, 2024). Performance measures such as first-contact resolution (FCR) typically provide guidance on resolution success. Specifically, the proportion of inquiries resolved by first contact that did not contain follow-up. A common benchmark in many other industries for the success of modern contact centres is that they achieve an FCR rate between 70% and 80% (Tirulo et al., 2026). As more calls are resolved, customer satisfaction is likely to increase, and the workload decreases. Equally significant in inquiry handling is average handling time (AHT) which measures the total time taken to process an interaction—consisting of both conversation time and post-interaction logs. Since agents or systems have lesser handling time, contact centres are constantly trying to manage AHTs without sacrificing service (Panda, 2024). Yet, extreme focus on speed risks undermining service results, especially when questions revolve around intricate and/or emotionally loaded matters for which communication and context should play a vital role.

Customer inquiries dealing procedures also have escalation mechanisms that are initiated when the primary service outlet has failed to satisfactorily address the issue. Escalation arises from lack of information, technical limitation, unhappy clients and managerial consent. Where traditional service escalation often meant sending the interaction down to a senior agent or department (Cai & Chi, 2018). In AI-based contact centres, escalation most often involves an automated machine handing the interaction over to human agents. Escalation will provide resolution accuracy. But it brings also higher operational costs and can disturb continuity in customer experience. New technology has added still more dimensions to the complexities of handling customer inquiries (Akande & Oyana, 2025). They must also link communications between communication channels in order to maintain steady stream and avoid the disruption posed by digital platforms. Contact centres can only achieve omnichannel service strategies by integrating interactions between these multiple channels of communication. An inquiry might be asked by a customer via a chatbot, followed by a telephonic conversation conducted with a human agent (Ghosh et al., 2024).

The handling of inquiries in these kinds of environments depends on the preservation of contextual continuity and the prevention of re-presentation of the same information, for repeat data giving is often noted to have a substantial impact on customer dissatisfaction (Arnold et al., 2023). Plus, customer expectations in terms of service speed and customization have risen dramatically in the last years. Surveys reveal that more than seven in ten customers expect answers when they reach out to a service provider using digital channels – consistent with the general shift in society toward live communication in our society (Lemon & Verhoef, 2016). Contact centres must thus balance the efficiency of providing services with the opportunity to offer personalized assistance, especially for inquiries relating to complex service failures or emotive matters. If these customers' expectations are not met, they may perceive service as less than high quality, mistrust the service provider, and be at risk of leaving.

C) Inquiry Complexity in Customer Service

The complexity of inquiries is a key aspect that plays a role in the effectiveness of automated customer service systems. In contact centre environments, inquiries vary dramatically in the cognitive effort, contextual comprehension, and problem-solving capabilities required to resolve questions (Inavolu, 2024). Consequently, inquiry complexity can be attributed to the degree to which a customer query involves ambiguity, multiple issues, contextual dependencies, or non-routine problem-solving requirements that exceed standard automated systems' structured response (Xu et al., 2020). When requests to support a customer do not yield simple information results or established work processes, in service environments, the complexity comes into play.

Common, routine inquiries tend to involve systematic questions and known answers, like checking account balances, verifying order status, or requesting basic product information. Since these queries generally follow a certain format and can be solved using predefined scripts or knowledge bases, they tend to be easy to scale into AI-based systems (Li et al., 2023). Unlike an inquiry that is straightforwardly answered, a complex inquiry often demands explanation, reasoning into context, this requires complex problem solving and multi-step reasoning. Often, such situations involve the client receiving non-standard-service requests that deviate from standard service procedures or involve multiple problems, incomplete information, and a variety of potential issues (Nisa et al., 2026).

Several factors are among the many factors contributing to the complexity of customer queries. The main source of complexity is ambiguity that is, when a customer's requests are not well understood or can be taken in various ways. Vague language or problem descriptions that involve ambiguous expressions need interpretation and understanding, or at least require some understanding and explanation, and automated systems have trouble executing those operations (Chauhan & Sagar, 2021). Another reason is that a specific interaction has multiple issues on it. Customers typically aggregate multiple requests or issues in a single query, and service agents are expected to prioritize, sequence, and address multiple problems at the same time (Gavrila et al., 2023). A multi-issue structure such as this requires higher levels of cognition in the interaction process and limits the effectiveness of standardized automated responses.

The context is also a source of complexity. Many customer inquiries are predicated on contextual knowledge pertaining to past engagement, account history, or situational information not specifically conveyed in the conversation. Understanding context and integrating information from multiple sources are essential to addressing these questions (Jain & Rani, 2026). The non-routine requests add to the complexity of the inquiry. These are the special needs type of requests, unique conditions, exceptions to standard policies, and those which create problems requiring creative problem-solving rather than simple rule-based solutions.

From a theoretical standpoint, the complexity of inquiry is explained via information processing theory, which postulates that the organization's ability to resolve problems depends on its capacity to process and interpret information (Mariani et al., 2023). In the context of customer service, the organization must handle more difficult, more complicated queries. Whereas human agents can depend on experience, judgment, and contextual reasoning, automated systems commonly operate on some predefined set of rules and structured knowledge bases. Consequently, they are unable to analyse complex or vague questions.

D) Limitations of AI in Handling Complex Inquiries

Though artificial intelligence is evolving quickly in customer care settings, AI systems still encounter serious limitations when responding to complicated customer queries. Automated agents like chatbots and voicebots primarily process structured requests and respond based on predefined intents, rules, or trained patterns. Although these systems can successfully respond to routine and repetitive requests, they lose effectiveness when such interactions require contextual understanding, flexible reasoning, or multi-step problem solving (Reda, 2024).

A great limitation of AI systems is its understanding of natural language. Most conversational AI models today are designed to identify typical customer intentions, but they might also fail to work as well if the customers' requests have ambiguous or other unusual meanings (Chau et al., 2025). Clients frequently report their concerns in colloquial language, and these are incomplete and/or in the use of indirect phrases, so automated analysis can be hard because these often require interpreting the problem informally (Vunnava, 2025). An example of this would be where the AI agent fails to know if customer intends to ask, and so an appropriate response will not appear which means the consumer should need to be sent to a human agent to reply.

So, another challenge has to do with contextual reasoning. In-depth customer queries, meanwhile, often rely on contextual details not contained in one message (Jain & Rani, 2026). For instance, dealing with a customer problem may necessitate expertise in previous engagement, account history, or the context of the request. Human agents usually understand that context and adjust their responses. On the other hand, AI systems may depend on limited conversational memory or prearranged data structures, limiting the integration of contextual information between user-to-user dialogue points (Dobbala & Lingolu, 2024).

AI systems can also have limitations around resolving multi-issue questions. Customers often lump their own numerous concerns on top of one with one service when they interact, they are expecting the service agent to identify and resolve each of these. But on average, automated systems tend to be designed to treat one intent at a time (Brown et al., 2024). In the presence of more than one problem the AI agent might wrongly rank one request ahead of others and will send responses that are incomplete or inappropriate. This restriction compels escalating to the attention of human agents who may concurrently take care of multiple sides of the problem.

Further, automated, customer service systems do not have the human agents ability to make adaptive judgments and flexibility to solve problems. A large number of customer service scenarios contain exceptions to standard procedures, requests for special consideration or problems requiring creative solutions. Human agents are there to take note of such experiences, to interpret organizational policies and make judgments as needed (Doellgast et al., 2023). AI systems, however, are normally bound by prescribed rules and their training data, and so have a harder time coping with non-standard service work.

Lastly, AI devices show that they have little or no ability to deal with emotional or sensitive customer interaction either. Customer inquiries usually concern frustration, complaints or just plain dissatisfaction with past service encounters. Human agents can pick up on emotional indications of emotion and provide empathetic responses, be they with reassurance or strategies for a negotiation that de-escalate the situation (Svari & Olsen, 2012). On the other hand, automated systems commonly concentrate on information processing rather than emotional interpretation, and as such, have potential problems with managing emotionally charged interactions.

These shortcomings highlight the limits of automation in customer service scenarios. While AI solutions significantly improve efficiency in handling routine and standardized inquiries, complex customer problems often exceed the operational capabilities of automated agents (Singh & Singh, 2024). As a result, escalation to human agents is still a requisite in many automated contact center systems, especially when inquiries involve ambiguity, contextual dependencies, multiple issues or a general need to solve non-routine problems.

E) Inquiry Complexity and Escalation in AI-Based Customer Service

From a customer point of view, customer queries inside a contact center may differ materially in the degree of comprehension, contextual thinking, and problem-solving which one needs to achieve meaningful resolution. Some interactions involve clear and predictable interactions, whereas others have ambiguous requests, multivalent issues, or contextual dependencies making them more difficult to process (Saberi et al., 2017). These variations lead to variability as to how well the systems automatically handle customer questions without human intervention.

Most automated customer service systems work based on intent identification and predefined systems of responses. This method enables AI agents to quickly complete routine interactions with customer requests that are clearly stated and follow standardized processes of service (Chinnaraju, 2025). But the success of such systems tends to be undermined when the customer queries involve more complicated information. The nature of these requests, those with multiple problems, indirect descriptions or context, necessitate interpretation beyond the reach of automated systems. Contact center operations frequently escalate to human agents under situations where automated systems are dealing with experiences beyond their processing capacity (Gelbrich et al., 2025). They are not just capable of responding to complex problems, they are also able to ask clarifying questions, interpret contextual information, and apply flexible reasoning. Therefore, the complexity of a customer inquiry influences whether an automated system can successfully solve the interaction or whether human intervention is necessary.

H1: Customer inquiries with higher levels of complexity are more likely to be transferred from AI agents to human agents in automated contact centers.

Complex inquiries raise the informational and interpretative levels that automated systems must handle (Tirulo et al., 2026). The above is particularly important when the customer interaction is complex, may include complicated terminology, multi-issue information, and contextual dependencies, as automated systems often become incapable of identifying the intent of the customer or providing a relevant solution. Interactions with heightened complexity are thus likely to elicit escalation mechanisms and be escalated to human agents who are better equipped to interpret and resolve the issue (Zhu et al., 2026).

Inquiry complexity also elucidates why certain forms of automated interaction cause escalation and others resolve satisfactorily. Because most interactions are routine requests corresponding to established intents, automated systems perform well. But as the level of complexity of the inquiry increases, the automated system faces a lower level of response (Singh & Singh, 2024). In this sense, complexity is the way in which automated interactions end in escalation to human agents, the operational limits of AI automation at the contact centers.

III. RESEARCH METHODOLOGY

A) Research Design and Context

This research uses a quantitative empirical design to inquire on the impact of inquiry complexity on increased customer inquiries within the AI-enabled contact center. Quantitative research is suitable for this investigation, with its potential to conduct analysis of large interaction data and recognize statistically significant associations between inquiry characteristics and service outcomes. The analysis is derived from interaction data from an automated contact center system within the telecommunications industry. The system employs AI-based automated service agents, specifically voicebots and chatbots intended to answer customer queries prior to handing off customers to human agents when necessary. They leverage intent recognition models and predefined response structures for responding to customer requests.

Considering the diverse range of customer inquiries in contact centers across the telecommunications industry, it is only natural that such inquiry-based customer service automation be implemented through the use of AI. In this case, customers often reach out to service providers about billing or technical assistance, service activation, and account management. Consequently, telecommunication contact centers shift to automated systems to handle mass volumes of routine interactions while moving more complex cases to human service representatives. The study tries to investigate how inquiry complexity impacts the likelihood of an AI-managed customer interaction being passed on to a human agent, by examining interaction data produced in this operational environment. That context provides a useful case for reviewing the operational constraints of automation in contact center service processes.

B) Data Collection and Preparation

We analyze interaction data coming from an automated contact center functioning in the telecommunications sector. The dataset includes 9,177 customer interactions that are undertaken by AI-based automated service agents, which can be voicebots or chatbots. The sample of actual customer services from September 2025 to December 2025 is large enough to represent a relatively large sample of customer service interactions. In a structured interaction log form, the interaction data was extracted from the contact center's operational system.

In the dataset, the individual observations each correspond to a customer inquiry, and provide information about what the interaction consisted of and what happened. These variables were the date and time of interaction, communication channel, market, category of inquiry, topic intent, escalation status, handling time, and an appropriate complexity score for the inquiry.

The dataset was preprocessed and prepared for empirical analysis to establish the consistency of the data prior to analysis. First, the dataset was evaluated to screen for incomplete or inconsistent records and the interactions with omitted relevant information were filtered out of the analysis. Second, the categorized inquiry categories and topic intents were verified for consistency of identification by observation. Finally, the escalation variable was checked and reported as one binary variable indicating that interactions handed over to a human agent were coded as “Yes” and interactions fixed by the automated system were categorized as “No”. Hence after the above-mentioned preparation steps the dataset obtained was structured and reliable for statistical study of the relationship with increasing complexity of inquiries in AI-based contact center environments and escalation.

C) Variable Operationalization and Analytical Method

Specifically, this study focuses on the relationship between inquiry complexity and the escalation of customer inquiries to a human agent in an AI-powered contact center environment. The above-mentioned hypotheses were evaluated by operationalizing the core variables reported in the dataset based on the data gained from interaction logs. The dependent variable of this study is customers transfer of inquiry to human agents as operationalized by the escalation indicator defined in the dataset. This variable determines whether interactions processed by the automated system were resolved correctly, or transmitted to a human service representative. As statistical analysis, escalation was treated as a binary variable, interactions transferred to a human agent were encoded as 1 (Yes) and interactions resolved by the automated system were coded as 0 (No). The main explanatory variable in the analysis is inquiry complexity. In the dataset, complexity is expressed on a scale from 0 to 10, with the higher values suggesting the need for greater interpretation, contextual understanding, or multi-step problem-solving. In this case, this captures the relative difficulty of customer inquiries and is the principal variable for how complexity reflects on escalation results.

A few control variables were included to compensate for possible differences across interaction characteristics as well as these variables. These variables include the communication channel used in the interaction (voicebot or chatbot), the inquiry category, and the time of the interaction. These variables will help insure that the relation between complexity and escalation in inquiries and the way it plays out in the contact center is independent of other operating factors in the contact center setting.

The analysis of the data is performed with a number of quantitative methods. Descriptive statistics are employed in the first step to summarize the key features of the data collection, such as the distribution of inquiry complexity and the average rate of escalation. Second, binary logistic regression analyses are implemented to analyze the effect of inquiry complexity on the probability to transfer an interaction to an actionable human agent. Logistic regression is suitable because the dependent variable in our study is binary. Finally, a mediation analysis is conducted to answer how inquiry complexity accounts for the relationship between automated customer service interactions and escalation outcomes.

Statistical analyses were performed using IBM SPSS, which supports estimation of logistic regression models and mediation effects over a large number of interaction datasets. By analyzing these data with these analytical methods we design an organized way of studying the test hypotheses and understand how AI-based automation reaches its operational limits in contact center environments.

IV. EMPIRICAL ANALYSIS & RESULTS

A) Dataset overview

The empirical approach used in this research is based on interaction-level data harvested from an AI-enabled contact center in the telecommunications industry, with the identity of the company kept confidential for privacy and data protection reasons. The dataset comprises 9,177 customer interactions recorded in four months, September to December 2025. All voice and chat interactions were automatically handled by service agents and either resolved or transferred to human agents.

Every observation contained in the dataset is an example of a single customer inquiry involving a record of the interaction, both behavioral and outcome. It is written in interaction logs, comprising operational and contextual variables on a customer request for each customer request. The variables present in the dataset are the communication channel (voicebot or chatbot), market, inquiry category, topic intent, escalation status, handling time, and a numerical measure of inquiry complexity.

The escalation variable shows if an interaction was passed to a human agent after being processed in the automated system. This variable is the main outcome of interest in the analysis. Further, the complexity score from 1 to 10 is used to indicate the amount of complexity involved in each customer inquiry. Larger values suggest interactions that require more elaboration, context-awareness, or multi-step problem-solving.

Overall, the dataset offers insights within customer service interactions with an automated contact center, with the potential to investigate the degree to which inquiry characteristics shape service outcomes. This is due to a relatively large sample size and detailed interaction-level data, which allows for tracking of escalation behavior patterns and the criteria under which automated systems reach their operational limits.

B) Descriptive Statistics

The dataset contains 9,177 customer interactions with 30.8% leading to escalation to a human agent and 69.2% resolved by the automated system. Consequently, AI-based service agents are able to process most customer queries, while a significant percentage still needs human intervention. Interactions are evenly distributed across service channels. About 51.2% of interactions were with voicebots and 48.8% with chatbots. This balanced distribution helps to make the dataset inclusive of these two categories of automated customer service interactions, and for any comparison among channels. These distributions are summarized in Table 2.

The average complexity score (1-10) of inquiry complexity is 4.34 with a standard deviation of 2.50. The observed values range from 1 (low complexity) to 10 (high complexity), so this indicates that customers' difficulty with a given inquiry varies greatly. This variation is crucial for the analysis to see how the variation of complexity affects escalation outcomes depending on the level and the complexity. The descriptive statistics for the numerical variables are presented in Table 1.

Table 1: Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Complexity	9177	1	10	4.34	2.496
Handling Time (in seconds)	9177	30	1197	228.98	151.220

Table 2: Frequency Distribution

	Frequency	Percent
Escalation		
Not escalated	6354	69.2
Escelated	2823	30.8
Channel		
Voicebot	8224	89.6
Chatbot	953	10.4
Market		
Croatia	2208	24.1
Romania	3742	40.8
Slovakia	3227	35.2
Total	9177	100.0

C) Distribution of Inquiry Complexity

The complexity variable is measured on a 1 to 10 scale, where the mean is 4.34 and the standard deviation is 2.50, meaning the overall dispersion of the variables is moderate. This indicates that client queries are not grouped at a particular level of difficulty, but instead, they can vary significantly in terms of the cognitive and informational resources needed for an answer.

The distribution indicates that a major percentage of the interactions tend towards the low to medium complexity value range (around 2–6), reflecting that the bulk of customer inquiries processed through the automation system require relatively systematic and easy-to-handle requests. Simultaneously, the dataset contains a significant amount of interactions with higher complexity levels (7–10), which are probably based on unclear answers, more than one problem or other contexts of dependencies. Although the occurrence of such high-complexity cases is relatively low, they are of special significance in this analysis as they are the cases in which the automation systems' limits might be questioned more often.

The histogram of the complexity variable shows that the scale of the distribution is slightly right-skewed, with lower and mid-level complexity values more frequent, and observations occurring less frequently as the complexity increases. This is characteristic of ordinary contact center settings, where routine (standard) inquiries comprise the bulk of interactions, with highly complex requests being a smaller but critical subset of customer requests.

Of great importance to the dataset, observations can be seen over the entire scale, giving it an overview of both simple and extremely complex requests. This variation is crucial for the empirical analysis as it enables a comprehensive analysis of the consequences of increasing levels of inquiry complexity on the probability of having the inquiry escalated to human agents. The histogram of the complexity variable shows the distribution of inquiry complexity shown in Table 3.

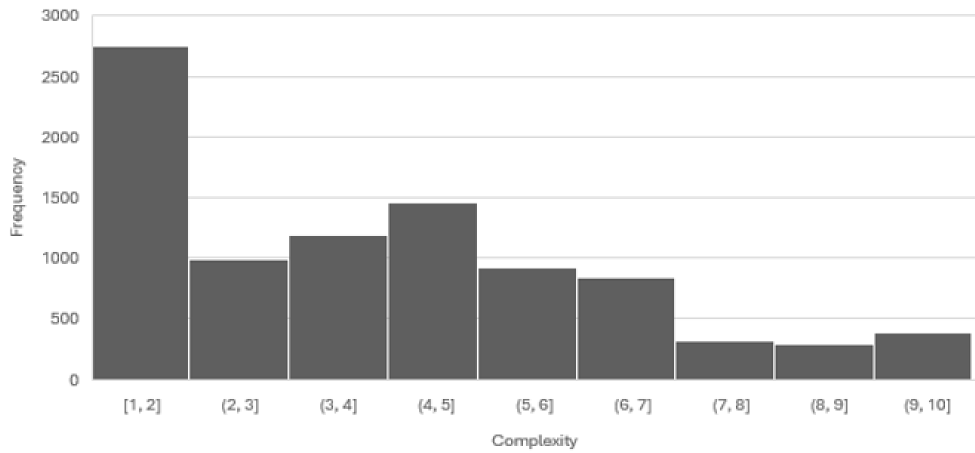

Figure 1. Distribution of Inquiry Complexity (Histogram)

D) Escalation Patterns by Inquiry Complexity

The analysis shows a clear and consistent pattern; the probability of escalation increases drastically with the increased complexity of the inquiry. Escalation rates are still fairly low at low levels of complexity. For instance, the inquiries with complexity levels of 1 and 2 demonstrate escalation rates of 5.3% and 6.9%, respectively, demonstrating that most simple interactions are auto-solved successfully by systems.

Escalation rates increase markedly with increasing complexity. At intermediate points of complexity (e.g., level 5), the escalation rate is about 29.9%, which means around one in three of these interactions will need human intervention. This trend is increased at the highest levels of complexity. For example, complexity 6 questions result in an escalation rate of 51.3%, indicating that more than half of the interactions are passed to human agents.

Thus, at the top level of the complexity scale, escalations become the dominant outcome. Inquiries of complexity levels 7 and 8 with escalation rates 65.5% and 64.5%, and levels 9 and 10 of 76.4% and 87.0%, respectively. These results suggest that very complex customer inquiries are rarely addressed by automated systems and almost always require human intervention.

Ultimately, the findings also show a well-defined positive correlation between inquiry complexity and escalation. As the complexity of the inquiry increases, escalation rates also increase. This observation leads one to the idea of the possible existence of a threshold effect in which automated systems work well only for less complicated requests but fail progressively when requests become more intricate or beyond a certain threshold.

This relationship is statistically significant (chi-square test a highly significant connection between inquiry complexity and escalation, $p < 0.001$). This result supports the proposition that differences in escalation rates by complexity level are not due to random variation. As a result, these findings provide strong empirical support that inquiry complexity is one of the most important considerations in determining whether AI-based systems are able to effectively handle a customer contact or require human participation. The results are summarized in Table 4, depicting the distribution of escalation rates by levels of inquiry complexity.

Table 4: Escalation Patterns by Inquiry Complexity

			Escalation_bin		Total
			Not escalated	Escalated	
Complexity	1	Count	1282	72	1354
		% within Complexity	94.7%	5.3%	100.0%
	2	Count	1301	97	1398
		% within Complexity	93.1%	6.9%	100.0%
	3	Count	796	199	995
		% within Complexity	80.0%	20.0%	100.0%
	4	Count	974	217	1191
		% within Complexity	81.8%	18.2%	100.0%

	5	Count	1027	438	1465
		% within Complexity	70.1%	29.9%	100.0%
	6	Count	447	471	918
		% within Complexity	48.7%	51.3%	100 .0%
	7	Count	292	554	846
		% within Complexity	34.5%	65.5%	100.0%
	8	Count	114	207	321
		% within Complexity	35.5%	64.5%	100.0%
	9	Count	70	227	297
		% within Complexity	23.6%	76.4%	100.0%
	10	Count	51	341	392
		% within Complexity	13.0%	87.0%	100.0%
Total		Count	6354	2823	9177
		% within Complexity	69.2%	30.8%	100.0%

E) Logistic Regression Analysis

In order to explore the connection between inquiry complexity and escalation probability, a binary logistic regression analysis was performed. This approach is suitable considering that the outcome variable is binary (0 = resolved by AI, 1 = transferred to a human agent).

The regression analysis shows that inquiry complexity has a statistically significant positive effect on the probability of escalation. As indicated in Table 5, the inquiry complexity coefficient is positive (B = 0.546) and significant ($p < 0.001$), which shows that the more complex the questions are, the greater the odds that they can be transferred to human agents.

The odds ratio (Exp(B) = 1.726) shows that with a one-unit increase in the complexity of the inquiry, the odds of escalation are expected to increase by 72.6%. This reflects a large effect size, suggesting that complexity plays a significant role in determining escalation outcomes in AI contact center settings.

For the model performance, the regression has a good overall fit. The Nagelkerke R^2 (0.354) indicates that the model accounts for ~35.4% of the variance in escalation outcome. Furthermore, the model also achieves an overall classification accuracy of 78.0%, implying that the model is capable of accurately predicting whether a customer inquiry is escalated based on its complexity or not.

An extended model that incorporates the communication channel as a control variable was also estimated to determine if the relationship observed is robust. Results indicate that the influence of inquiry complexity is strong and statistically significant, while the channel variable has no significant effect on escalation. It also further backs up the notion that complexity is the main driver of escalation in automated customer service interactions.

Logistic regression analysis provides empirical evidence that the complexity of inquiry is a major determinant of escalation behavior. The findings confirm that the complexity of customer queries leads to a substantial increase in the likelihood that automated systems will not solve them, meaning a higher probability of transferring the problems to human agents.

Table 5: Logistic Regression Analysis

Variables in the Equation		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Complexity	.546	.013	1822.555	1	<.001	1.726
	Constant	-3.440	.071	2371.422	1	<.001	.032

F) Hypothesis Testing

H1 stated that customer inquiries with a high level of complexity would more easily be transferred from AI agents to human agents in automated contact centers. This hypothesis is bolstered by the findings of this analysis.

An increasingly complex inquiry implies a predictable high rate of escalation. In particular, escalation rates rise from 5.3% at the lower complexity level to 87.0% at the higher complexity level, suggesting a significant difference across levels of inquiry difficulty. The chi-square test demonstrated further that this relation is statistically significant ($p < 0.001$).

The logistic regression analysis results back this up. The complexity of inquiry positively and significantly affected escalation risk ($B = 0.546$, $p < 0.001$). So the odds ratio implies that a one-unit increase in complexity increases the probability of escalating by approximately 72.6%, which means the overall effect of variation increased by just 1 unit with a strong effect size. Control variables were included that did not modify the significance of the complexity variable.

H1 is, therefore, supported based on these findings. The results further suggest that inquiry complexity is a central component of the success of resolving customer interactions with an AI-based system or transferring this contact to a human agent. The empirical evidence as a whole heavily supports the claim that AI-based automation can take over contact center functions, but this claim is highly constrained as the customer questions are complex.

V. DISCUSSION

A) Discussion of Findings

Based on the empirical analysis, the correlation between inquiry complexity and the probability of escalation from AI solutions to on-the-ground agents is strong. The probability of escalation for an interaction being transferred increases to almost universal levels as complex cases increase, from the very low levels of transfer for a simple inquiry. This pattern provides clear evidence that inquiry complexity is among the most determinant factors in determining the overall effectiveness of automated customer service systems.

A central concept in these findings is that AI-based systems perform well at handling routine, structured customer enquiries, but as interaction complexity increases, their performance deteriorates. At less complex levels, where customer inquiries are clearly defined and patterned, automated systems learn to understand intentions well enough and give appropriate responses. But as inquiries worsen, especially those involving uncertainty, multiple problems, or context-bound relationships, the ability of AI systems to accurately process and resolve interactions declines. With that comes an increased chance of escalating to human agents who are more prepared to deal with situations like this.

The observed escalation pattern is in close alignment with the theoretical arguments presented in the literature on limitations on AI in customer service environments. Chen et al. (2024) have demonstrated that AI systems cannot understand the context of language input, and that, even with improvements in natural language processing, models for this task still struggle to interpret ambiguous inputs, integrate contextual information into the model, and handle multi-step problem-solving tasks. This study presents empirical evidence to confirm these limitations. It shows that as the informational and cognitive requirements of customer inquiries rise, automated systems will be challenged more beyond their operational limits.

Moreover, these findings align with information processing theory, which proposes that the extent to which a system can solve problems depends on the information it integrates. As customer service is more complex, information processing is required for interpreting information in incomplete or vague form, including integrating information or information based on situational cues, and adapting to the need for flexibility (Mariani et al., 2023). While human agents can do these things with the help of experience and good judgment, AI systems are typically limited because they're trained from predetermined models and are fed data in a set format (Fürst et al., 2025). The high correlation between complexity and escalation in the analysis shows that this processing capacity difference is not only visible but also quite substantial.

The second important finding of the results is the presence of a threshold effect, where escalation rates increase sharply beyond certain reasonably high levels of complexity. It indicates that a point may be reached at which an autonomous system is no longer an effective problem solver and needs our intervention. Operationally, this means that automated systems should not treat all customer inquiries equally (Rashid & Kausik, 2024). If nothing else, getting high-complexity interactions identified and routed earlier in the process may allow for better efficiency and customer experience.

B) Theoretical Implications

The results of this study are able to add to the literature in relation to AI-based customer service and service automation by providing evidence on the impact of inquiry complexity on service outcomes. Although existing studies have typically highlighted the efficiency merits and demerits of utilizing artificial intelligence in customer service settings, this research provides empirical evidence that inquiry complexity serves as an important predictor of escalation behavior in the case of automated contact centers.

First, by demonstrating that AI systems are not effective for all customer encounters, the study adds to the literature on service automation. The results suggest that the automation performance highly depends on the task, with respect to complexity. This is consistent with the emerging literature, which indicates that AI systems are most suitable for repetitive, routine, and high-frequency applications, while more nuanced service tasks still require human intervention (Zhao & Wu, 2025). By establishing empirically high-quality, large-scale data obtained from real interaction data, this study supports the proposition that the demarcations of automation are task-based rather than all-or-nothing.

Second, the results add to the existing literature on AI limitations in customer service domains by providing a mechanism by which to account for why automated systems are unable to meet certain challenges in a particular domain. Instead of treating AI limitations as a general constraint, the results show a systematic negative correlation between failure and higher degrees of inquiry complexity. This offers a more precise perspective on the limitations of AI, treating them as responses to informational and cognitive demands rather than simply technological limitations. The study thus adds to the literature on complex and nuanced representations of AI performance in the service sector.

Third, the research helps establish the empirical basis for information processing theory in AI-powered service systems. The link between complexity and escalation results stems from the fact that problem-solving effectiveness is influenced by the processing and interpretability of information. As customer inquiries are more complicated, it is difficult for automated systems to handle informational needs, and the reliance on human agents increases. We hope this finding reaffirms the applicability of information processing theory as a helpful perspective to understand the relationship between human and machine agents in the service field.

Lastly, the work adds to the body of knowledge on human–AI cooperation by underscoring the unique functions of automated and human agents in contact centers. These findings indicate that AI and human agents are not replacements but rather work in a task-based division of labor with automated systems managing basic questions and humans handling complex issues. This perspective is consistent with recent work on hybrid service models and provides empirical evidence for constructing systems that harmonise automation with human knowledge (Mangipudi, 2025).

C) Managerial Implications

This study's findings carry some significant implications for the practice world and for contact center managers, and AI system developers at large, on how to implement automation in customer service environments.

To begin, this result indicates that inquiry complexity ought to be paramount in contact center operations design. Escalation rates tend to increase with complexity, so not all customer contacts should go through the same process. Instead, contact centers can enhance efficiency by making use of complexity-based routing systems in which simple questions are routed through AI agents and complex ones are delivered directly to human agents or escalated earlier in the interaction process. It minimizes unwarranted interaction time, as well as improves resolution rates and overall service throughput (Mahajan & Gupta, 2023).

The results also underline the necessity for prompt identification of difficult questions. AI can be further improved by using measures to detect signs of complexity, including ambiguous language, multiple intents, or repeated user inputs. By picking up these signals early, the system can also push timely escalations to human agents, avoiding customer frustration and ensuring that automated customer interactions do not go wrong. This implies that organizations investing in AI-driven customer service solutions will want to prioritize the enhancement of complexity detection ability (Zahidi et al., 2024).

Third, the results suggest that organizations should consider implementing a hybrid service model, where AI agents and humans serve within a complementary rather than a replacement role. Although automated systems work very well for simple and daily routine inquiries, human agents are the best substitute for complex, context-sensitive, and non-routine inquiries. Thus, managers need to optimize the interaction between the AI and human agents, making sure that there is no haggling in communication between the automated and human service channels (Mangipudi, 2025).

Fourth, there are considerations in resource distribution and the workforce. Since convoluted matters are likelier to be escalated, complexity can serve as a prediction of the overall demand of human agents. It gives it a chance to use those more realistic staffing options to determine if and how to allocate its human resources, especially as peak demand occurs or when markets need to take on more complex types of inquiries (Chauhan & Sagar, 2021).

Lastly, the result shows that organizations should examine the constraints of automated systems, the possible limitations of some of the AI systems employed at the organizations. Automation delivers significantly higher efficiency and lower costs, but relying heavily on AI to handle complex inquiries risks ruining the customer experience. For example, customers may experience frustration due to unaddressed issues or repeated automated interactions failures, causing dissatisfaction or churn. Hence, managers should balance automation with the help of humans as best as possible to support them, so customers are able to avail themselves of assistance depending on the complexity of their inquiries (Alhajri et al., 2026).

In general, the results highlighted that automation of contact center management in the context of digitalization is not only the implementation of the AI technology but also the strategic concept of when automation is appropriate and when it is required by humans in order to manage the contact center management.

D) Limitations

Though the empirical results are strong, the study does come with several important limitations that need to be taken into account in interpreting the findings. For one, the analysis has drawn upon data from a single contact center in the telecommunications industry. While such context offers a rich and relevant dataset, it can reduce the generalization of findings to other industries. Customer inquiries in industries like banking, healthcare, e-commerce, etc., may vary greatly in their structure and complexity, which can have an impact on an AI-based system's performance and the escalation risk.

Secondly, the investigation uses a set of inquiry-complexity criteria, calculated as numerical scores within the dataset. Even though this approach offers common ground and an accurate means of quantifying complexity, it is not necessarily representative of complexity in its entirety (e.g., emotion, customer sentiment, and contextual effects). However, the operationalization of complexity used in this study is, in itself, only one small part of the whole.

Third, the date period for the dataset was (September to December 2023). Even though the sample sizes are large, the results are representative of customers interacting within the particular context of the study time frame. Factors such as seasonality, changes in customer behavior or updates to the AI that affect the findings could potentially be influenced by a longer observation period.

Fourth, the study examines mostly AI-triggered interactions before escalation without any details regarding human agent performance in the post-transaction environment. Consequently, the study does not include a full service process/service escalation analysis or results to assess whether escalated interactions were resolved.

Lastly, although the study recognizes a robust link between inquiry complexity and escalation, it fails to incorporate all potential factors potentially affecting escalation decisions. These effects can also be influenced by system design, training data quality, or organizational policies, but these factors cannot be observed directly in the dataset and are not discussed in detail in the dataset.

E) Future Research

The results of this research offer a range of opportunities for future research on AI-based customer service and the limitations of automation in contact centre environments. First, the study could expand further by covering a range of industries as well as service contexts. Since this study concerns the telecommunications sector, it is important to explore potential patterns of inquiry complexity and escalation across banking, healthcare, e-commerce, and travel sectors. Cross-industry comparisons would provide a wider view of the extent to which the nature of customer inquiries affects the efficiency of AI systems.

Second, additional exploration of additional aspects of inquiry complexity as an additional dimension beyond this numerical measure should be encouraged for further research. Emotional complexity, for instance, customer frustration or dissatisfaction, could provide a better understanding of situations where AI systems are less effective. In the same way, if the field of linguistic complexity or conversational dynamics was analyzed, it could show more fully the overall issues in the automated systems.

Third, future studies can explore the implications of the design and learning of AI systems in complex inquiries. As these artificial intelligence technologies continue to develop, it may be useful to test whether more sophisticated models, better training data, or greater contextual memory can reduce the degree of escalation. To learn from previous interactions, longitudinal studies could examine how the performance of AI systems evolves over time.

Fourth, the interaction between human agents and automated systems could be examined more holistically, using hybrid service models as a lens. We could examine the timing of escalation, the quality of handover, and the interaction between AI and human agents, and their impact on customer satisfaction and service efficiency. This would lead to a better understanding of how to maximize human–AI collaboration in contact centers. Finally, further studies might include customer-level outcomes like satisfaction, retention, and perceived service quality to see how escalation decision-making impacts these outcomes on the whole. Although this is an operational outcome-based study, it would be useful to connect escalation behavior to the customer experience in the academic literature and managerial applications.

VI. CONCLUSION

The present study sought to investigate the limits of AI automation in contact centers by investigating a core question that under what conditions do automated systems fail to resolve customer inquiries and require escalation to human agents? The study wanted to particularly understand how inquiry complexity may be a shaping factor of these results. As businesses lean on chatbots and voicebots for an increasing number of customer interactions, finding the edges of automation, both as an academic and as a management issue, becomes a critical issue (Doellgast et al., 2023). To understand the complexity of complex interaction data on the effectiveness of an automated service system, this study studied its impact empirically.

Using a data set of 9,177 customer interactions, the analysis collected was from an AI-enabled contact center in the telecommunications industry. The data spanned four months from September to December 2025 and covered interactions done by voicebots and chatbots. Each observation is a one-off customer inquiry, which provides information on both the nature and result of the interaction, escalation status, and the complexity for inquiries from 1 to 10. The application of interaction-level data offered a rigorous and sound way to explore actual service behaviors and not a self-reported perception or theoretical scenario.

The research results demonstrate, in strong and reliable evidence, the involvement of inquiry complexity as one of the most determining factors on escalation in the automated contact center context. There was a definite and consistent trend of progression across all levels of analysis: as customer questions became more complicated, the chances of an encounter moving to human agents became higher. The rate of escalation remains low at lower complexity levels, suggesting that AI systems are well adapted to common, well-defined interactions. Yet as complexity increases, escalation rates have a marked increase; eventually, they reach a point where most interactions will require human intervention. Such a pattern demonstrates that the performance of AI systems highly depends on the task characteristics, including the level of cognitive and informational demand.

Statistical analysis confirms this. The logistic regression analysis has demonstrated a strong and highly significant effect of inquiry complexity on escalation. An increase in inquiry complexity by a unit greatly increases the likelihood that an interaction will be passed to a human agent. The size of this phenomenon underscores the importance of complexity in establishing operating limits of AI-based automation. Additionally, the model accounts for a significant amount of the variance in escalation outcomes, suggesting that complexity alone is an important measure of whether or not the automated system can successfully resolve a customer inquiry. These results demonstrate that AI effectiveness in contact centers is not universal but is contingent. Automation is very good at handling routine, well-defined and repetitive tasks: for such scenarios, they are capable of processing high volumes of interactions in a time-efficient manner, which can result in low operational cost and increased responsiveness. But their performance plummets when presented with intricate questions that include uncertainty, multiple themes, contextual dependencies, or non-routine issues when solving them. In such cases, AI systems are limited, and humans are required for intervention.

Theoretically, the findings from this study provide empirical evidence on this topic concerning service automation and AI in customer service by correlating inquiry complexity directly to escalation, and these results are meaningful from a scientific standpoint; they also add to the existing literature on this topic. Instead of thinking of AI limitations as a universal or abstract concept, the results suggest that these limitations are systematically connected to the information requirements of customer interactions.

These results add support to a closer scrutiny of when and why automated systems fail, situating complexity as a main construct in the explanation of limitations to automation. The findings also reinforce the significance of information processing theory concerning AI-enabled service systems. Through a lens of complexity-oriented logic, one may argue, the solution to problems has much to do with the ability to process and interpret information. As the complexity of the inquiry increases, the task's information needs exceed those of such bots, increasing the risk that the action will escalate. Unlike intelligent systems, human agents have more flexibility, contextual awareness, and judgment to handle complex and ambiguous situations (Olabiyi et al., 2025). This inherent difference in processing capabilities between human agents and artificial ones correlates with the observed relationship of complexity and escalation.

Moreover, the results support the idea that AI and human agents function in a complementary, not a substitutive, relationship. For example, automated systems are very valuable for routine interactions while human agents deal with complex cases. This suggests what is required, instead of absolute automation, the future of customer service is in well-designed hybrid systems of artificial intelligence and human intelligence. Consequently, organizations must learn to draw boundaries between automated and human-handled interactions (Fürst et al., 2025).

The research has several key points of management merit. To be clear, not all customer inquiries are perfect for automation. It is this kind of dehumanization where you treat all interactions as good for automation, that is the biggest problem with the product, because not all inquiries are created equal, and for every challenge we face, a result, customer experience will always be a struggle. Instead, organizations should use systems that analyze the complexity of upcoming enquiries and route them accordingly. By handling tasks such as simple queries with intelligent AI systems and complicated cases with human agents, organizations can work efficiently and offer better quality services (Alhajri et al., 2026).

Second, the results reinforce the value of detecting intricacy in an earlier stage of the interaction. AI models that can recognize this type of complexity, such as language that is ambiguous or has many possible intentions, trigger timely escalation in the system, avoiding repetitive and useless automation in the first place (Rangu, 2025). It leads not only to better operational efficiency but also to higher customer satisfaction, as much frustration is lifted from the company and response times are reduced again.

Thirdly, the results suggest that companies should guard against relying on automation too much. Attempting to automate complex-to very complex interactions, without properly protected automation procedures, leads to unfavorable customer experience and less-than-good service. A balanced mix of automation with human help is thus crucial.

Despite the contributions the study offers, it is not without its limitations. The analysis itself concentrates on one particular company in the telecommunications industry, which may not easily generalize the findings to other fields. The measure of inquiry complexity, while useful, may not encompass all aspects of complexity, especially emotional or contextual dimensions, which make quantitative evaluation difficult. Furthermore, the study focuses on interactions before escalation and does not consider the outcomes of human-assisted interactions following transfer. These limitations imply that the results should be considered as being more specific to the study. This work can be extended to develop other relationships in other sectors, consider further layers of complexity, and consider how AI advances may expand the borders of automation in the future. Research, including customer satisfaction and service quality measures, would contribute to a better understanding of the consequences of escalation decisions. Additionally, exploring the interaction of humans and AI agents in hybrid service networks may help us to better coordinate the collaboration between automated and human service channels.

To conclude, this study shows that the complexity of inquiry is the crucial factor that determines the constraints of AI-driven automation within the contact centers. Automated systems perform so well for mundane tasks that they are highly effective, but as complexity increases, customer inquiries in their response time decrease dramatically. Thus, escalating to human agents does not reflect a failure of the system per se, but instead is an inevitable characteristic of technology, which highlights the limits of how much automation can be performed. In exploring the role of complexity, this research offers more nuanced insights into the role of AI in customer service, bridging the gap from analysis of the role of automation to its application to service delivery in the contact center today.

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