American University Kyiv

A Capstone Project

ASSESSING THE IMPACT OF KNOWLEDGE-SEEKING PRACTICES, COLLABORATION, AND AI TOOLS ON TICKET ESCALATION IN HEALTHCARE IT SUPPORT: A LOGISTIC REGRESSION ANALYSIS

ОЦІНЮВАННЯ ВПЛИВУ ПРАКТИК ПОШУКУ ЗНАНЬ, СПІВПРАЦІ ТА ІНСТРУМЕНТІВ ШТУЧНОГО ІНТЕЛЕКТУ НА ПРОЦЕС ЕСКАЛАЦІЇ ЗВЕРНЕНЬ У СФЕРІ ІТ-ПІДТРИМКИ ОХОРОНИ ЗДОРОВ’Я: ЛОГІСТИЧНО-РЕГРЕСІЙНИЙ АНАЛІЗ

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ABSTRACT

This study investigates the factors influencing the escalation of support tickets to programmers in a healthcare IT environment. The research focuses on three key factors: knowledge-seeking practices (use of requirements and documentation), cross-team consultation, and the use of artificial intelligence (AI) chatbot. In addition to escalation frequency, the study also examines the concept of valid escalation, defined as cases where escalation is justified and confirmed as a system defect, deficiency or enhancement.

A quantitative research approach was applied. The analysis was conducted using logistic regression on a dataset of 150 support tickets, enabling the evaluation of both main and interaction effects of the selected factors on escalation outcomes.

The results indicate that knowledge-seeking practices have a statistically significant impact on both escalation and valid escalation. Specifically, the use of requirements increases the likelihood of escalation while improving the accuracy and validity of escalation decisions. In contrast, cross-team consultation and AI tools do not demonstrate a statistically significant independent effect. However, the interaction between requirements and AI chatbot is significant, suggesting that AI chatbot can reduce escalation when combined with structured documentation.

The findings highlight that effective technical support is not solely achieved by reducing the number of escalations, but by improving their correctness and justification. Based on these results, the study recommends strengthening knowledge management practices, improving documentation quality and accessibility, and enhancing AI tools through integration with system requirements. Overall, the research contributes to a better understanding of escalation processes and provides practical recommendations for optimizing support operations in healthcare IT systems.

Keywords: healthcare IT support, technical support, ticket escalation, valid escalation, escalation process, support ticket resolution, knowledge-seeking practices, knowledge management, requirements, cross-team collaboration, artificial intelligence, AI chatbot, logistic regression, effective support.

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CHAPTER 1. INTRODUCTION

In product-oriented IT companies, technical support is a critical department that significantly influences overall business performance. This is particularly relevant in organizations developing healthcare applications, where system reliability and timely issue resolution are essential. As a Technical Support Specialist in a company that provides healthcare software solutions across the United States, Europe, and Australia, I work directly with client-reported issues submitted through support tickets.

These tickets vary in urgency, complexity, and subject matter. While some issues require escalation to software developers, others can be resolved within the technical support team. Reducing unnecessary escalations is an important organizational objective, as developer involvement is significantly more costly. Minimizing escalations not only reduces operational costs but also allows developers to focus on creating new features and improving existing products, which contributes to long-term revenue growth.

However, the process of ticket resolution and escalation is influenced by multiple factors. In this study, three key factors are identified as having the most significant impact: the use of internal documentation (such as knowledge bases and system requirements), cross-team collaboration, and the use of an internally developed AI chatbot.

The effective use of documentation helps support specialists better understand how the system is expected to function and identify potential issues more efficiently. Collaboration also plays an important role, as consulting with colleagues or other teams can provide additional expertise and support more effective problem-solving. With the increasing adoption of AI technologies, our company has developed its own AI chatbot to assist in ticket investigation. The use of this tool may significantly influence both the efficiency and effectiveness of issue resolution.

The primary objective of this capstone project is to identify which factors, or combinations of factors, most significantly influence the likelihood of ticket escalation to developers. Specifically, this study aims to answer the following research question:

How does the use of AI chatbot, knowledge-seeking practices, and cross-team consultation affect the likelihood of ticket escalation to programmers in healthcare IT application support?

To address this question, a sample of support tickets from a defined time period will be analyzed. Each ticket will be evaluated based on the presence of key factors, including the use of knowledge bases and system requirements, collaboration with team members and colleagues from other departments, and the application of AI chatbot. The outcome of each ticket, whether it was escalated or resolved within the support team, will also be recorded. In addition, it will be assessed whether the escalation is valid.

This quantitative approach aims to provide data-driven insights into effective support practices. The findings are expected to offer practical recommendations for improving support efficiency, reducing unnecessary escalations, and optimizing resource allocation within the organization. Ultimately, enhancing these processes can lead to increased productivity, improved service quality, and better business outcomes.

CHAPTER 2. LITERATURE REVIEW

The primary focus of the reviewed literature is to investigate the factors that influence the effectiveness of technical support. The selected works provide a comprehensive overview of methods and technologies that enhance IT service delivery, streamline ticket resolution, and support knowledge sharing among IT professionals. Key research areas explore how AI technologies can be effectively applied to support work, moving from the simple automation of repetitive tickets to providing intelligent, context-aware recommendations for complex technical problems. By examining the intersection of human expertise and machine intelligence, these studies establish a theoretical framework for modernizing the service desk into a proactive, high-efficiency environment.

Knowledge Management in service desk environments plays a critical role in improving service quality and organizational competitiveness. Dostál and Skrbek (2020) analyze various methods, tools, and techniques that support knowledge management processes within IT support functions. The authors structure these approaches according to key phases of the knowledge management cycle, including knowledge creation, sharing, and application.

The study highlights that effective use of knowledge bases, documentation, and structured knowledge-sharing practices enables faster incident resolution and reduces service costs. Additionally, collaboration mechanisms such as training, communities of practice, and expert interaction enhance knowledge transfer within service desk teams. The authors also emphasize the growing importance of artificial intelligence tools, such as recommender systems and expert systems, in optimizing knowledge retrieval and decision-making processes. Overall, Dostál and Skrbek (2020) conclude that integrating appropriate knowledge management practices into service desk operations significantly improves efficiency, customer satisfaction, and the overall performance of IT support services.

Ahmed (2020) examines the critical role of Problem Management within the IT Service Management (ITSM) framework, distinguishing it from Incident Management by its focus on investigating root causes rather than merely restoring service. The author outlines a dual approach to managing IT issues: reactive management, which responds to specific incidents, and proactive management, which analyzes historical trends to identify and resolve potential problems before they disrupt business operations.

A central theme of Ahmed's research is the lifecycle of a "Known Error" and the utilization of the Known Error Database (KEDB). The author argues that documenting workarounds and root cause analysis (RCA) reports is essential for organizational knowledge transfer. Furthermore, the study details the technical escalation path, moving from Level 1 (L1) customer interaction to Level 3 (L3) subject matter experts, which aligns with the need to optimize resource allocation by ensuring complex issues are handled by the appropriate technical tier. Ahmed (2020) concludes that well-implemented problem management processes enhance service desk efficiency, reduce escalation frequency, and improve overall IT service performance.

Artificial Intelligence is increasingly being applied to incident management in IT operations. Jiang et al. (2023) present Xpert, a system that leverages large language models (LLMs) to improve incident management by providing intelligent query recommendations. According to Jiang et al. (2023), using LLM-driven recommendations supports faster and more accurate problem diagnosis and resolution because it reduces the cognitive load on human agents and enhances the retrieval of past incident knowledge. By systematically integrating query suggestions into incident workflows, Xpert enables support teams to access relevant resources and insights more effectively than traditional search-based or manual methods. The study highlights the potential of advanced AI techniques, particularly LLMs, to transform incident management practices in IT service environments by improving efficiency and decision support.

Naveen Koka (2024) examines the role of artificial intelligence in improving ticketing systems and customer service operations. The author argues that AI significantly enhances efficiency by automating routine processes such as ticket categorization, assignment, and initial troubleshooting. Through machine learning algorithms, tickets can be intelligently routed based on agent expertise, availability, and urgency, which reduces response time and optimizes resource allocation. Overall, the study demonstrates that integrating AI into ticketing systems leads to improved scalability, reduced operational costs, and higher service quality, making it a critical factor in modern IT service management.

Deepa K. Iyer (2024) analyzes the impact of artificial intelligence on IT service desk optimization, emphasizing its role in improving operational efficiency, service quality, and cost management. The author highlights that traditional service desks often struggle with high ticket volumes, manual processing, and delayed response times, which reduce overall effectiveness. In contrast, AI-driven ticketing systems utilize machine learning, natural language processing, and predictive analytics to automate ticket classification, prioritization, and routing.

Iyer (2024) demonstrates that AI integration significantly enhances performance by reducing ticket resolution times, improving SLA compliance, and enabling proactive identification of recurring incidents. Additionally, AI-powered tools such as chatbots and self-service systems empower users to resolve routine issues independently, further reducing workload on support teams. However, the study also identifies key challenges, including data quality issues, integration with legacy systems, and resistance from staff.

Aluwala (2023) investigates the application of artificial intelligence in IT incident management, emphasizing how AI technologies such as machine learning, natural language processing, and predictive analytics can optimize IT service delivery. The study highlights that conventional incident management methods are often insufficient for complex IT environments, resulting in delayed resolutions and resource inefficiencies. AI-based systems automate key tickets, including ticket classification, routing, root cause analysis, and repetitive workflow execution, thereby improving mean time to resolve (MTTR) and overall service desk productivity.

The study by Crosley and Wasito (2023) investigates the application of AI-driven ticket classification to improve IT support efficiency. The research underscores that AI-driven approaches can streamline IT support by automating ticket classification and prioritization, reducing reliance on human judgment, shortening response times, and enhancing overall efficiency. The study also identifies potential future improvements, including expanding datasets and iterative model retraining.

Despite the large number of studies on the effectiveness of technical support, critical gaps remain unaddressed. In recent years, there has been a significant surge in research exploring AI-driven service desk optimizations. While substantial attention has been given to AI technologies, there is a notable lack of research on the fundamental importance of knowledge bases and the specific requirements for maintaining these systems. Current literature does not fully address how knowledge base usage and accurate documentation contribute to improved ticket resolution, nor does it sufficiently examine the role of inter-team collaboration.

Another major gap exists in the application of AI. Existing studies primarily examine how AI can assist in managing tickets, such as categorizing, routing, or reducing ticket creation, rather than investigating how AI tools can directly help support specialists resolve complex issues independently. Evidence is limited regarding the use of AI as a tool to prevent the necessity of escalating tickets to programmers.

Finally, no study has comprehensively explored how these factors – AI technologies, knowledge base utilization, and cross-team collaboration – interact as an integrated ecosystem to influence the escalation process. It remains unclear whether the combined effect of these variables significantly reduces escalation frequency or whether they operate independently. This research aims to fill these gaps by investigating how the synergy of human collaboration, knowledge management, and AI-driven support can minimize technical escalations and optimize the work of support teams.

CHAPTER 3. METHODOLOGY

This chapter describes the research methodology used to investigate the factors influencing ticket escalation in healthcare IT support. It outlines the research design, data collection procedures, variables, and statistical methods applied in the study. The methodology is designed to evaluate the impact of knowledge-seeking practices, cross-team consultation, and the use of AI chatbot on escalation outcomes. A quantitative research approach was adopted to systematically analyze relationships between these factors and the likelihood of ticket escalation.

The ***Main Research Hypothesis*** is that specific technical and collaborative factors significantly influence the likelihood of ticket escalation to programmers in healthcare IT application support.

To evaluate this, the study will test the following specific hypotheses:

- ***H1:*** Knowledge-seeking practices significantly influence the likelihood of ticket escalation to programmers.
- ***H2:*** Cross-team consultation reduces the likelihood of ticket escalation to programmers.
- ***H3:*** The use of AI chatbot reduces the likelihood of ticket escalation to programmers.

In addition to these hypotheses, the study will examine potential interaction effects between the factors to determine whether combinations of these practices have a significant joint influence on escalation outcomes.

Quantitative analyses will be used to gain a comprehensive understanding of technical support investigation practices. The quantitative component will focus on identifying relationships between selected factors and escalation outcomes.

3.1 Selection of the Response Variable

In this research, two response variables have been identified:

Escalation – This serves as the primary dependent variable. As it has a significant impact on resolution time and the costs associated with application support, analyzing escalation occurrences allows for the assessment of escalation frequency and its effect on overall workflow efficiency.

Valid Escalation – This additional response variable assesses whether escalations were truly necessary. It distinguishes between necessary and unnecessary escalations by indicating whether an escalated ticket was confirmed as an actual defect or enhancement.

Table 1

Experimental Responses

Symbol	**Type of Response**	**Response Name**	**Description**
y_1	Binary Response (Performance)	Escalation	Indicates whether a ticket was escalated to programmers **(1 = Yes, 0 = No)**
y_2	Binary Response (Quality)	Valid Escalation	Indicates whether an escalated ticket was confirmed as a valid defect or enhancement **(1 = Valid, 0 = Not Valid)**

3.2 Choice of Factors and Levels

Three main factors that could impact the escalation and efficiency of ticket resolution have been identified. These factors will be systematically tested during the analysis. Each factor has two levels: the presence or absence of the factor (e.g., yes or no). Below is a description of the selected factors and their potential influence on reducing unnecessary escalations:

1. **Use of Requirements and Knowledge Base (x_1)**

Factor Description: System requirements, documentation, and knowledge bases provide essential information about expected system behavior. In some cases, issues perceived as defects may actually represent intended functionality. These resources may also contain information about necessary configurations and detailed descriptions of system features, helping specialists better understand how the system operates. Reviewing these materials enables support specialists to resolve issues independently or make more informed escalation decisions. Escalated tickets will be reviewed to assess whether the support specialist referenced relevant requirements in the ticket.

Levels:

- **$x_{1.1}$ (Yes / 1):** The support specialist referenced system requirements or knowledge base materials in the ticket.
- **$x_{1.2}$ (No / 0):** No reference to requirements or documentation was identified.

2. **Cross-Team Consultation (x_2)**

Factor Description: Given the wide range of issues that may arise, it is common that a support specialist may not have the solution to every problem. Consulting colleagues within the support team or other teams, such as business analysts, software engineers, teams supporting other products, or testing teams, can help identify potential solutions. This collaboration could potentially reduce escalations by providing quicker resolutions. Escalated tickets will be reviewed to determine whether the specialist turned to other teams or support members for advice before escalating the issue to programmers.

Levels:

- **$X_{2.1}$ (Yes / 1):** The support specialist consulted colleagues or other team members (excluding programmers) before escalating the issue.
- **$X_{2.2}$ (No / 0):** No consultation with colleagues or other teams before escalating to programmers.

3. Use of AI Chatbot (x_3)

Factor Description:

The use of AI tools is becoming increasingly common in technical support environments. Such systems can assist in error analysis, retrieval of relevant information, and the suggestion of potential solutions. In particular, our internal AI chatbot trained on historical support tickets can provide context-aware recommendations based on previously resolved issues. In this study, escalated tickets will be analyzed to determine whether support specialists utilized an AI chatbot during the investigation process.

Levels:

- **$X_{3.1}$ (Yes / 1):** The support specialist used AI chatbot during the investigation process.
- **$X_{3.1}$ (No / 0):** No AI chatbot was used.

Table 2

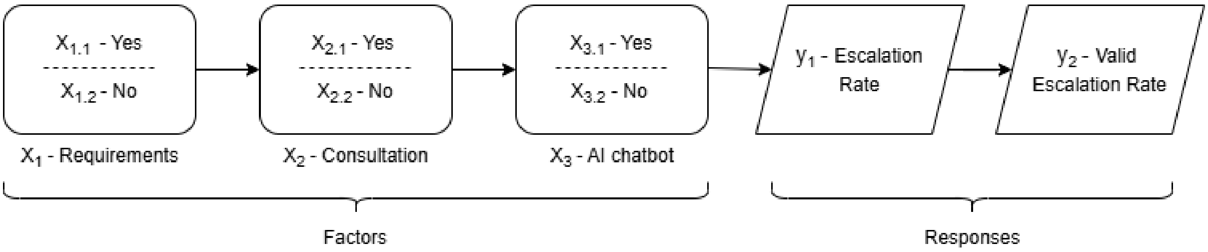
Summary Table of Factors and Levels

Symbolic designation of factor	Name of the factor	Designation and description of the levels of the factor
x_1	Search for requirements	$x_{1,1}$ – Support specialist checks system requirements/knowledge base $x_{1,2}$ – No search for requirements/knowledge base
x_2	Consultation with Other Colleagues	$x_{2,1}$ – Consultation with colleagues before escalation $x_{2,2}$ – No consultation before escalation
x_3	Using AI chatbot	$x_{3,1}$ – Support specialist used AI chatbot $x_{3,2}$ – Support specialist doesn't use AI chatbot

The relationship between the responses and factors is presented in the scheme (see Figure 1).

Figure 1

Conditional Representation of the Influence of Studied Factors on Responses



Although the experiment focuses on the three factors above, random uncontrollable factors might also influence the escalation process.

3.3 Choice of Experimental Design

A factorial experimental design was selected for this study. A factorial experiment examines how multiple factors influence a specific outcome, known as the response variable. Each factor is tested at defined levels, and the design includes all possible combinations of these levels across the factors.

This experimental design is particularly appropriate for the current study, as it allows for the simultaneous examination of multiple factors that may influence ticket escalation. Since the research aims to evaluate not only the individual effects of knowledge-seeking practices, cross-team collaboration, and AI chatbot usage, but also their potential interactions, a factorial design provides a structured and efficient approach. Additionally, the binary nature of the selected factors aligns well with a two-level design, enabling clear comparison between the presence and absence of each practice. This approach supports a comprehensive analysis of how these factors contribute to escalation outcomes both independently and in combination.

In this research, a two-level full factorial design (2×2×2) is applied, where each of the three factors is examined at two levels: presence and absence. Although two-level factorial designs do not allow for exploration of a wide range of factor values, they are efficient and effective for identifying key patterns and main effects with a relatively small number of observations. This makes them particularly suitable for exploratory studies aimed at understanding relationships between variables.

The study includes 150 support tickets handled by the technical support team between March 1 and March 30. To ensure a representative dataset, tickets were randomly selected from different days of the week, covering varying workloads and operational conditions.

To reduce bias and improve the generalizability of the results, the selected tickets:

- Were handled by different support specialists
- Covered a range of topics, products, complexity levels, priorities, and clients
- Represented various combinations of factor levels

To ensure data accuracy, ticket information, including escalation status and valid escalation confirmation, was extracted directly from the system database, minimizing the risk of manual data entry errors. Since all ticket-related activities are documented, each ticket was manually reviewed to verify the presence or absence of the selected factors.

For each ticket, the following data points were recorded:

- Whether system requirements or documentation were referenced
- Whether consultation with colleagues or other teams occurred
- Whether AI chatbot was used during the investigation
- Whether the ticket was escalated to programmers
- Whether the escalation was valid

The table below summarizes the possible combinations of factors included in the experiment.

Table 3

Possible Factor Combinations

Combination	Requirements (x_1)	Consultation (x_2)	AI chatbot (x_3)
1	0	0	0
2	1	1	1
3	1	0	0
4	1	1	0
5	0	1	0
6	0	1	1
7	0	0	1
8	1	0	1

3.4 Statistical Analysis

The next step involves analyzing the collected data using statistical software. To examine the effects of the selected factors and their combinations on ticket escalation, logistic regression analysis will be conducted.

Logistic regression is a statistical method used to model the relationship between one or more independent variables and a binary dependent variable. It estimates the probability that a given outcome occurs, in this case, whether a ticket is escalated to programmers (1) or not (0). Unlike linear regression, logistic regression applies a logistic (sigmoid) function to ensure that predicted probabilities fall within the range of 0 to 1. The results are typically interpreted in terms of odds ratios, which indicate how the presence of a factor increases or decreases the likelihood of the outcome.

In the context of this study, logistic regression is appropriate because the dependent variables (escalation and valid escalation) are binary, and the research design includes multiple independent variables. The method allows for the evaluation of both main effects and interaction effects, making it suitable for analyzing how knowledge-seeking practices, cross-team consultation, and the use of AI chatbot influence escalation outcomes individually and in combination.

The logistic regression analysis will be used to determine:

- The main effects of each factor on the likelihood of escalation
- The interaction effects between factors
- The statistical significance of these relationships

The significance of each factor will be assessed using p-values, with a threshold of 0.05. Additionally, odds ratios will be examined to interpret the direction and magnitude of each effect.

This approach provides a robust and appropriate framework for identifying which factors contribute most to reducing ticket escalation and improving ticket resolution efficiency.

CHAPTER 4. DATA AND ANALYSIS

4.1 Data Description

The experiment was conducted retrospectively using data from support tickets received between March 1 and March 30. During this period, technical support specialists were assigned tickets from various clients. The tickets covered a range of products and varied in priority and complexity. Additionally, the workload fluctuated throughout the period due to varying ticket volumes and staff availability (e.g., vacations), which contributed to capturing a realistic range of working conditions and external factors.

Technical support specialists involved in the study had different levels of experience and expertise. However, all specialists had access to the same resources, including internal documentation, knowledge bases, system requirements, and AI chatbot. They also had the ability to consult with colleagues or other teams for assistance, such as clarifying expected system behavior or resolving uncertainties before escalating tickets to programmers.

Data were extracted from an Oracle database, ensuring accuracy and completeness of the dataset. Since all actions and relevant information are documented within each ticket, a manual review was conducted to identify the presence or absence of the selected factors. Each ticket was analyzed and coded accordingly.

The execution of the study followed the planned methodology without significant deviations. All required data were successfully collected and verified, supporting the reliability and validity of the analysis.

Table 4 presents the results of the ticket analysis, including key data on escalation outcomes across different combinations of factor levels. This dataset forms the basis for evaluating the impact of knowledge-seeking practices, cross-team consultation, and the use of AI chatbot on the likelihood of ticket escalation.

Table 4

Tickets review results

Ticket	Escalation	Valid Escalation	Requirements	Consultation	AI chatbot
1	0	0	0	0	0
2	0	0	0	1	0
3	1	0	0	1	1
4	0	0	0	0	0
5	1	1	1	1	0
...	...	...	...	...	...
147	0	0	1	0	0
148	1	0	0	1	0
149	0	0	0	0	0
150	1	1	0	0	0

4.2 Statistical analysis of the data

The statistical analysis of the data from Table 4 aims to identify which of the three main factors, as well as their combinations, significantly influence the likelihood of ticket escalation. The analysis includes both descriptive statistics and logistic regression, conducted using JASP software. Descriptive statistics are used to summarize the distribution of escalation outcomes across different factor levels, while logistic regression is applied to assess the significance of the main effects and interaction effects of the factors on escalation. This approach enables the identification of the most influential factors affecting the effectiveness of ticket resolution.

4.2.1 Descriptive Statistics

Descriptive statistics were used to summarize the dataset by describing its central tendency and variability. For each variable (requirements usage, consultation, use of AI tools, escalation and valid escalation), the following metrics were calculated:

1. Mean (Average)

The mean represents the average value of a variable across all observations. For binary variables (coded as 0 = No, 1 = Yes), the mean can be interpreted as the proportion of cases in which the factor is present.

2. Standard Deviation

The standard deviation measures the variability or dispersion of the data. In the context of binary variables, it reflects how much variation exists between the presence (1) and absence (0) of a factor across observations.

3. Minimum

The minimum represents the smallest observed value in the dataset. Since all variables are binary, the minimum value is 0, indicating the absence of a factor.

4. Maximum

The maximum represents the largest observed value in the dataset. For binary variables, the maximum value is 1, indicating the presence of a factor.

The following table presents the descriptive statistics for the key variables:

Table 5

Descriptive Statistics

	Requirements	Consultation	AI chatbot	Escalation	Valid Escalation
Valid	150	150	150	150	150
Missing	0	0	0	0	0
Mean (arithmetic)	0.287	0.347	0.120	0.453	0.260
Std. Deviation	0.454	0.478	0.326	0.499	0.440
Minimum	0.000	0.000	0.000	0.000	0.000
Maximum	1.000	1.000	1.000	1.000	1.000

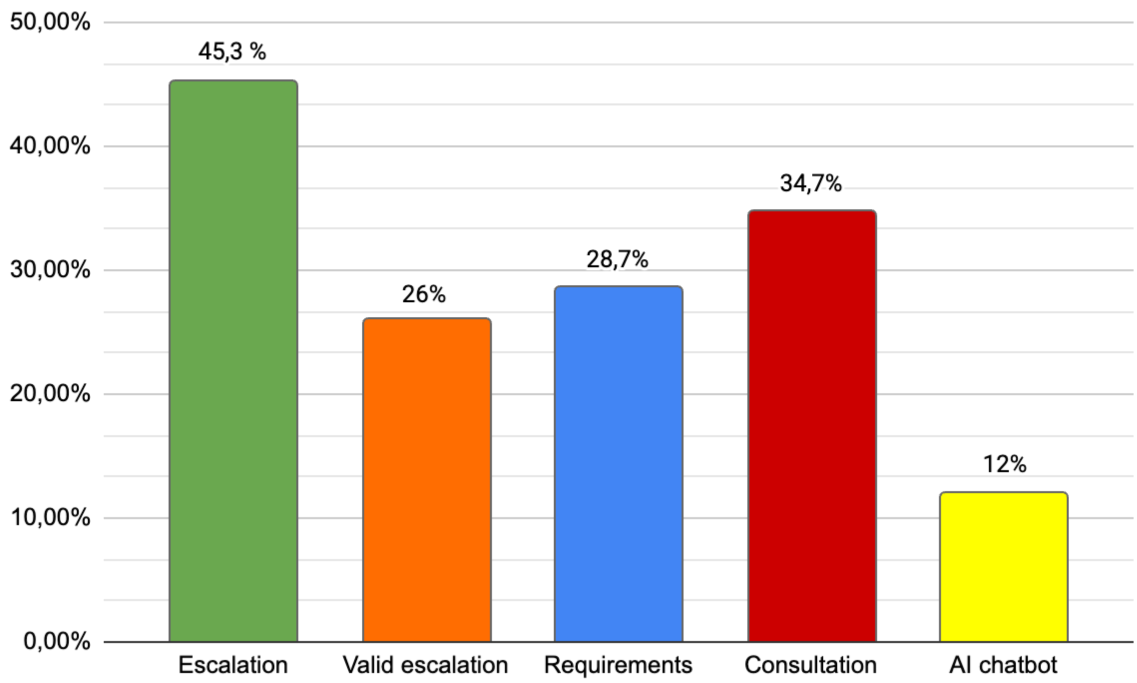
Descriptive statistics were calculated to summarize the distribution of the variables included in the study.

All variables contain 150 valid observations with no missing data, indicating a complete dataset suitable for analysis.

Since all variables are binary (0 = No, 1 = Yes), the mean values can be interpreted as proportions, representing the frequency with which each factor occurred.

Figure 2

Distribution of Technical Support Factors and Escalation Outcomes



Requirements: The mean value for requirements usage is 0.287, indicating that system requirements or documentation were used in approximately 28.7% of the analyzed tickets. The standard deviation of 0.454 suggests moderate variability in the use of documentation across tickets.

Consultation: For consultation, the mean is 0.347, meaning that specialists consulted colleagues or other teams in about 34.7% of cases. The standard deviation (0.478) reflects a relatively high variation, indicating that consultation practices differ across tickets.

AI chatbot: The AI chatbot was used less frequently, with a mean of 0.120, showing that it was applied in only 12.0% of tickets. The lower standard deviation (0.326) suggests less variability, consistent with its relatively infrequent use.

Escalation: The overall escalation rate has a mean of 0.453, meaning that 45.3% of tickets were escalated to programmers. The standard deviation (0.499) is relatively high, reflecting a near-balanced distribution between escalated and non-escalated tickets.

Valid escalation: Regarding the outcome variables, the mean value for valid escalation is 0.260, indicating that 26.0% of tickets were escalated appropriately. The standard deviation (0.440) shows moderate variation in these cases.

For all variables, the minimum value is 0 and the maximum value is 1, which is expected given their binary nature.

4.2.2 Logistic Regression

Logistic regression is a statistical method used to model the relationship between one or more independent variables and a binary dependent variable. It estimates the probability that a specific outcome occurs, in this case, whether a ticket is escalated to programmers (1) or not (0). Unlike methods that compare group means, logistic regression focuses on how predictor variables influence the likelihood of an outcome.

In this study, logistic regression was conducted using JASP software to identify which individual factors, as well as their combinations, significantly influence the likelihood of ticket escalation and probability of valid escalation.

The model estimates regression coefficients (β) for each factor, which indicate the direction and strength of the relationship with the dependent variable. These coefficients can be transformed into odds ratios, which show how the presence of a factor increases or decreases the probability of escalation.

The analysis includes:

- Main effects, representing the individual impact of each factor
- Interaction effects, representing the combined influence of two or more factors

Statistical significance is assessed using p-values for each coefficient. A significance level of 0.05 was adopted in this study:

If $p < 0.05$, the factor is considered to have a statistically significant effect on escalation

If $p \geq 0.05$, the factor is not considered statistically significant

This approach allows for the identification of the most influential factors and their interactions, providing insights into how different practices contribute to reducing ticket escalation.

Logistic Regression for Escalation

Two logistic regression models were estimated in JASP. The first model (Model 1) included only the main effects of the three predictors: Requirements, Consultation, and AI chatbot. This model was used to examine the individual impact of each factor on the likelihood of ticket escalation. The results are presented in Table 6.

Table 6

Logistic Regression Results for Escalation (Model 1: Main effects)

						Wald Test		
Model		Estimate	Standard Error	Odds Ratio	z	Wald Statistic	df	p
M_0	(Intercept)	−0.267	0.227	0.766	−1.175	1.381	1	.240
	Requirements	0.793	0.377	2.211	2.102	4.418	1	.036
	AI chatbot	−0.176	0.530	0.839	−0.332	0.110	1	.740
	Consultation	−0.378	0.358	0.685	−1.057	1.117	1	.291
M_1	(Intercept)	−0.403	0.245	0.668	−1.648	2.715	1	.099

The results of Model 1 indicate that Requirements had a statistically significant effect on escalation ($p = .036$). The corresponding odds ratio ($OR = 2.21$) suggests that tickets associated with defined requirements are more than twice as likely to be escalated compared to those without requirements.

In contrast, Consultation ($p = .291$) and AI chatbot ($p = .740$) did not show statistically significant effects. This indicates that, when considered independently, these factors do not have a reliable influence on the likelihood of escalation.

Overall, the findings from Model 1 suggest that among the examined factors, only the presence of requirements plays a significant role in increasing the probability of escalation, while consultation and AI chatbot usage do not demonstrate a meaningful individual impact.

The second model (Model 2) extended the analysis by including interaction terms between the predictors (Requirements × AI chatbot, Requirements × Consultation, and AI chatbot × Consultation). This model was used to examine whether the combined presence of factors has a significant effect on the likelihood of ticket escalation beyond their individual contributions. The results are presented in Table 7.

Table 7

Logistic Regression Results for Escalation (Model 2: Interaction Effects)

						Wald Test		
Model		Estimate	Standard Error	Odds Ratio	z	Wald Statistic	df	p
M_1	(Intercept)	−0.403	0.245	0.668	−1.648	2.715	1	.099
	Requirements	1.103	0.524	3.012	2.104	4.426	1	.035
	AI chatbot	2.065	1.192	7.882	1.732	3.000	1	.083
	Consultation	−0.184	0.452	0.832	−0.407	0.165	1	.684
	Requirements * AI chatbot	−2.653	1.329	0.070	−1.996	3.985	1	.046
	Requirements * Consultation	−0.039	0.815	0.962	−0.047	0.002	1	.962
	AI chatbot * Consultation	−2.196	1.331	0.111	−1.650	2.721	1	.099

The results of Model 2 show that Requirements remained a statistically significant predictor of escalation (p = .035, OR = 3.01), indicating that the presence of requirements continues to increase the likelihood of escalation when interaction effects are considered.

Importantly, the interaction between Requirements and AI chatbot was also statistically significant (p = .046, OR = 0.07). This finding suggests that the combined effect of these two factors differs from their individual effects. Specifically, while requirements alone increase the likelihood of escalation, the presence of an AI chatbot appears to reduce this effect, indicating a moderating role of AI tools.

The interaction effects between Requirements and Consultation (p = .962) and between AI chatbot and Consultation (p = .099) were not statistically significant. This indicates that consultation does not significantly alter the relationship between the other factors and escalation.

Overall, the inclusion of interaction terms slightly improved the model fit compared to Model 1. In summary, Model 2 demonstrates that while requirements significantly increase the probability of escalation, the interaction between requirements and AI chatbot use suggests that AI tools may mitigate this effect when both are present. Other combinations of factors did not show a statistically significant influence on escalation outcomes.

The three-way interaction between Requirements, Consultation, and AI chatbot was not statistically significant ($p = .990$) and was associated with a very large standard error, indicating model instability. Therefore, this effect is not interpreted further.

Logistic Regression for Valid Escalation

In addition to analyzing overall escalation, a separate logistic regression analysis was conducted to examine the factors influencing valid escalation, defined as tickets that were correctly escalated and confirmed as defects or enhancements. The same set of predictors, Requirements, Consultation, and AI chatbot, along with their interaction terms, were included in the analysis using JASP.

Two logistic regression models were also estimated to analyze valid escalation. The first model (Model 1) included only the main effects of the predictors. The results are presented in Table 8.

Table 8

Logistic Regression Results for Valid Escalation (Model 1: Main effects)

						Wald Test		
Model		Estimate	Standard Error	Odds Ratio	z	Wald Statistic	df	p
M_0	(Intercept)	−1.392	0.277	0.249	−5.023	25.23	1	< .001
	Requirements	1.286	0.406	3.618	3.169	10.04	1	.002
	AI chatbot	−0.202	0.599	0.817	−0.336	0.113	1	.737
	Consultation	−0.206	0.414	0.814	−0.499	0.249	1	.618

The results indicate that Requirements had a statistically significant positive effect on valid escalation ($p = .002$, $OR = 3.62$). This suggests that tickets associated with defined requirements are more than three times as likely to result in a valid escalation compared to those without requirements.

In contrast, AI chatbot ($p = .737$) and Consultation ($p = .618$) did not show statistically significant effects. This indicates that, when considered independently, these factors do not significantly influence whether an escalation is valid.

Overall, Model 1 demonstrates that the presence of requirements is a strong and reliable predictor of valid escalation, while the other factors do not show meaningful individual effects.

The second model (Model 2) extended the analysis by including interaction terms between the predictors. The results are presented in Table 9.

Table 9

Logistic Regression Results for Valid Escalation (Model 2: Interaction Effects)

Model		Estimate	Standard Error	Odds Ratio	z	Wald Test		
						Wald Statistic	df	p
M_1	(Intercept)	−1.600	0.320	0.202	−5.004	25.04	1	< .001
	Requirements	1.682	0.540	5.379	3.116	9.712	1	.002
	AI chatbot	0.993	1.001	2.700	0.992	0.984	1	.321
	Consultation	0.341	0.540	1.406	0.631	0.398	1	.528
	Requirements * AI chatbot	−1.004	1.241	0.366	−0.809	0.655	1	.418
	Requirements * Consultation	−0.832	0.845	0.435	−0.984	0.968	1	.325
	AI chatbot * Consultation	−1.747	1.348	0.174	−1.296	1.680	1	.195

In this model, Requirements remained a statistically significant predictor ($p = .002$, $OR = 5.38$), further reinforcing its strong positive influence on valid escalation outcomes.

However, none of the interaction terms were statistically significant, including:

- Requirements × AI chatbot ($p = .418$)
- Requirements × Consultation ($p = .325$)
- AI chatbot × Consultation ($p = .195$)

This indicates that the combined presence of these factors does not significantly alter the likelihood of valid escalation beyond the effect of requirements alone.

The full model including the three-way interaction also did not yield significant results for interaction effects ($p = .989$) and showed signs of instability, as indicated by extremely large standard errors. Therefore, this interaction is not interpreted further.

Overall, the analysis of valid escalation shows a clear and consistent pattern that Requirements are the only factor that significantly increases the likelihood of correct (valid) escalation.

Neither consultation nor the use of AI chatbot tools, nor their combinations, demonstrated a statistically significant effect on valid escalation outcomes. This suggests that clearly defined requirements play a crucial role in ensuring that escalations are appropriate and justified.

CHAPTER 5. FINDINGS AND RECOMMENDED STRATEGIES FOR REDUCING TICKET ESCALATION

5.1 Key Findings

The aim of this study was to analyze the impact of requirements usage, cross-team consultation, and AI chatbot on ticket escalation and valid escalation using descriptive statistics and logistic regression. The results provide insights into the factors influencing escalation decisions and the effectiveness of different support practices.

The descriptive statistics indicate a moderate level of variation across the studied factors and outcomes. Consultation was the most frequently used support practice, followed by the use of system requirements, while the AI chatbot was used relatively rarely. At the same time, the escalation rate shows that nearly half of all tickets were escalated to programmers, whereas only about one quarter of all cases resulted in valid escalations.

The logistic regression analysis indicates that requirements have a statistically significant effect on escalation and valid escalation. This suggests that well-defined system requirements play an important role in the decision-making process and are strongly associated with escalation events.

In contrast, consultation and AI chatbot did not show a statistically significant independent effect on either escalation or valid escalation. This indicates that, when considered separately, these factors do not reliably influence escalation outcomes.

Regarding interaction effects, most combinations of factors did not show a statistically significant influence on escalation outcomes. However, the interaction between requirements and AI chatbot demonstrated a significant effect, suggesting that AI chatbot may modify the impact of requirements on escalation decisions.

5.2 Discussion and Implications

Based on these findings, the research hypotheses can be evaluated.

The results provide partial support for the main research hypothesis, confirming that specific technical and collaborative factors significantly influence the likelihood of ticket escalation to programmers.

The results support the first hypothesis, which states that knowledge-seeking practices significantly influence the likelihood of ticket escalation to programmers. The findings confirm that the use of requirements has a statistically significant effect on escalation outcomes.

At the same time, the second and third hypotheses are not supported. The results indicate that cross-team consultation does not significantly reduce escalation, and the use of AI tools alone does not significantly reduce escalation likelihood.

Overall, the findings support the main hypothesis that there are factors influencing the likelihood of ticket escalation to programmers in healthcare IT application support. In particular, knowledge-seeking practices, as well as the interaction between knowledge-seeking practices and AI chatbot usage, demonstrate a significant impact on the escalation process.

When answering the research question, the findings suggest that among the examined factors, knowledge-seeking practices, particularly the use of requirements and documentation, play the most important role in escalation processes. However, rather than reducing escalation, these practices are associated with an increase in escalation frequency, while simultaneously improving the quality of escalations, meaning that more escalated tickets are valid and correctly identified as defects or system enhancements.

This indicates that support specialists who actively use requirements and documentation tend to escalate issues more accurately. In other words, these practices do not reduce the number of escalations overall, but they improve the correctness and validity of escalation decisions.

This finding is particularly important in the context of healthcare IT systems, where accuracy, traceability, and adherence to system requirements are critical. Proper documentation ensures that systems behave according to strict specifications, and escalation decisions are made based on verified discrepancies rather than assumptions.

At the same time, the combination of requirements usage and AI chatbot shows a different effect. The results suggest that AI chatbot, that is based on historical ticket data, can help support specialists resolve issues independently. When used together with requirements, AI chatbot may reduce the likelihood of escalation by providing additional context, suggesting solutions, and enabling faster problem resolution without involving programmers.

Overall, the findings indicate that while knowledge-seeking practices increase the accuracy of escalation decisions, AI tools combined with structured requirements have the potential to reduce unnecessary escalations and improve independent problem-solving within the support team.

5.3 Recommended Strategies

Based on the findings of this study, several practical strategies can be proposed to improve ticket resolution efficiency and reduce unnecessary escalations.

1. Strengthening Knowledge Base and Requirements Management

The results show that knowledge-seeking practices, particularly the use of requirements and documentation, play the most significant role in the escalation process. Therefore, the company should prioritize the development and maintenance of high-quality documentation.

First, all system requirements should be clearly defined, complete, and consistently updated to reflect changes in product functionality. Since systems evolve over time, it is essential to ensure that documentation remains accurate and aligned with the current state of the product.

Second, documentation and knowledge bases should be centrally organized and easily accessible to all technical support specialists. A well-structured knowledge base reduces time spent searching for information and supports more effective decision-making.

Third, the company should invest in training programs to ensure that support specialists understand how to effectively use requirements and documentation in their daily work. This is especially important for new employees, as clear and structured documentation can significantly improve onboarding and reduce the learning curve.

Additionally, collaboration between support specialists, business analysts, and system architects should be strengthened to ensure that documentation reflects both technical accuracy and practical usability. Support teams should also be encouraged to contribute to the knowledge base by documenting recurring issues, troubleshooting steps, and best practices.

2. Enhancing AI Tools for Support Operations

Although AI chatbot did not show a significant independent effect, the results indicate that their combination with requirements reduces the likelihood of escalation. This suggests that AI chatbot can play a valuable supporting role when integrated with structured knowledge sources.

However, the findings also show that the AI chatbot is currently underutilized, being used in only 12% of analyzed tickets. This low adoption rate may limit its potential impact on the ticket resolution process. Since the tool is relatively new, it is recommended that support specialists receive additional training and guidance on how to effectively incorporate the AI chatbot into their daily investigation practices.

To improve its effectiveness, it is recommended to expand the data sources used by AI chatbot. Currently, the AI system relies primarily on historical ticket data. However, chatbot performance could be significantly enhanced by incorporating system requirements and official documentation into the AI knowledge base.

By combining historical issue resolution data with formal requirements, AI tools can provide more accurate, context-aware recommendations. This would enable support specialists to better understand system behavior and resolve issues independently, reducing the need for escalation.

3. Focus on Quality of Escalation

The findings indicate that the use of requirements increases the accuracy and validity of escalations, even if it does not reduce their overall number. Therefore, the company should shift focus from simply reducing escalation volume to improving the quality of escalation decisions.

In industries such as healthcare IT, where system correctness is critical, ensuring that escalations are justified and based on verified discrepancies is more important than minimizing their number.

Overall, the company should focus on:

- Improving the quality and accessibility of documentation
- Providing training on knowledge-seeking practices
- Enhancing AI tools through integration with requirements
- Encouraging knowledge sharing within support teams

By implementing these strategies, the organization can improve support efficiency, reduce unnecessary escalations, and ensure more accurate resolution of technical issues.

CHAPTER 6. LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

While this study provides valuable insights into the factors influencing ticket escalation, several limitations should be acknowledged, which also suggest directions for future research.

First, the study was based on a relatively limited sample size, consisting of 150 tickets collected over a short time period. Although this dataset allowed for identifying key patterns, a larger and more diverse sample would improve the statistical reliability and generalizability of the findings. Therefore, future research should include a greater number of tickets over an extended time period to enhance the robustness of the results.

Second, the analysis focused on a restricted set of factors, namely knowledge-seeking practices, cross-team consultation, and the use of AI chatbot. However, other variables such as support specialist experience, ticket complexity, priority level, and workload may also significantly influence escalation decisions. Future studies should incorporate these additional factors to provide a more comprehensive understanding of the escalation process.

Third, the evaluation of AI usage in this study was limited to an internal AI chatbot. While this reflects current organizational practices, it does not fully represent the wide range of AI tools available today. Modern AI technologies can assist with tickets such as log analysis, script generation, and advanced troubleshooting, which were not considered in this research. Future research should explore the impact of different types of AI tools, including external solutions, to better assess their role in improving ticket resolution and reducing escalation.

Finally, the study was conducted within a single support team in one organization, focusing on a specific healthcare IT product. As a result, the findings may not be fully generalizable to other teams, systems, or industries. Future research could extend this analysis to multiple organizations, different support teams, and various application domains to evaluate whether the observed relationships remain consistent across different contexts.

CHAPTER 7. CONCLUSION

This capstone project aimed to investigate the factors that influence the escalation of support tickets to programmers within a healthcare IT environment. The primary focus was on three key factors: knowledge-seeking practices (use of requirements and documentation), cross-team consultation, and the use of internal AI chatbot. In addition to escalation frequency, the study also examined the concept of valid escalation, defined as cases where escalation is justified and confirmed as a system defect, deficiency, or enhancement.

To achieve the research objectives, quantitative analysis was conducted using logistic regression, which is appropriate for modeling binary outcomes such as escalation (yes/no). This method enabled the evaluation of both main effects and interaction effects of selected factors.

The results of the quantitative analysis indicate that knowledge-seeking practices, particularly the use of system requirements and documentation, have a statistically significant impact on both escalation and valid escalation. Specifically, the presence of requirements increases the likelihood of escalation; however, it also significantly improves the quality and correctness of escalation decisions. This means that support specialists who actively use documentation are more likely to escalate tickets appropriately, ensuring that escalated cases are valid and justified.

In contrast, cross-team consultation and the use of AI chatbot did not demonstrate a statistically significant independent effect on escalation outcomes. However, an important finding emerged from the interaction analysis: the combination of requirements and AI chatbot significantly reduces the likelihood of escalation. This suggests that while AI tools alone may not be sufficient, their integration with structured knowledge sources can enhance problem-solving capabilities and support independent issue resolution.

The findings supported the main hypothesis that certain factors influence the likelihood of ticket escalation to programmers within healthcare IT support, demonstrating that escalation decisions are influenced by identifiable operational practices rather than occurring randomly. In particular, knowledge-seeking practices demonstrated a statistically significant effect on escalation outcomes, confirming the first hypothesis. Additionally, the interaction between knowledge-seeking practices and AI chatbot usage showed a significant influence on the escalation process, indicating that AI tools can be more effective when combined with structured documentation and requirements. However, the hypotheses related to cross-team consultation and the independent use of AI chatbot were not supported, as these factors did not demonstrate statistically significant individual effects on escalation likelihood.

Based on these findings, several practical recommendations were proposed. The most important direction for improvement is the enhancement of knowledge management practices, including maintaining accurate and up-to-date requirements, improving accessibility of documentation, and providing training for support specialists. Additionally, the study suggests further development of AI chatbot through integration with system requirements, rather than relying solely on historical ticket data. Moreover, since the results indicate that the AI chatbot is currently underutilized, increasing its adoption among support specialists should also be a priority. This can be achieved through targeted training, clear usage guidelines, and integration of the tool into standard investigation workflows. This combined approach has the potential to significantly reduce unnecessary escalations while maintaining high decision quality.

Overall, this research demonstrates that the effectiveness of technical support is not determined solely by reducing escalation frequency, but by improving the accuracy and justification of escalation decisions. In the context of healthcare IT systems, where reliability and correctness are critical, this distinction is particularly important.

In conclusion, the study contributes to a better understanding of how different operational factors influence escalation processes and provides actionable insights for optimizing support workflows. By focusing on knowledge utilization, improving documentation practices, and strategically enhancing AI tools, organizations can achieve more efficient and effective technical support operations.

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