American University Kyiv

A Capstone Project

EVALUATING THE OPERATIONAL IMPACT OF AI CHATBOTS AND OWNERSHIP STRUCTURE IN HEALTHCARE IT SERVICE MANAGEMENT

ОЦІНКА ОПЕРАЦІЙНОГО ВПЛИВУ ЧАТ-БОТІВ ЗІ ШТУЧНИМ ІНТЕЛЕКТОМ ТА СТРУКТУРИ ВЛАСНОСТІ В УПРАВЛІННІ ІТ-ПОСЛУГАМИ ОХОРОНИ ЗДОРОВ'Я

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ABSTRACT

The increasing adoption of artificial intelligence (AI) chatbots in healthcare IT Service Management (ITSM) is often framed as a broadly applicable approach for improving efficiency and reducing operational workload. However, limited empirical evidence exists regarding how organizational ownership structures and global time-zone separation influence the realized value of such technologies. This study examines the operational impact of AI chatbot deployment within a globally distributed healthcare IT support environment, focusing on investigation-phase support for specialized genetics systems.

Using a quantitative, quasi-experimental design, the study analyzes task-level metadata from an internal ticket management system across two six-month periods before and after AI implementation. The analysis combines longitudinal comparison of ticket volume, temporal latency modeling using Total Resolution Latency (TRL) and Lost Day Share of TRL, and interaction analysis using factorial ANOVA to assess the moderating role of ownership structure.

The results show that AI chatbot deployment is associated with reduced manual workload and lower asynchronous coordination delay. However, these improvements are not uniform. While average coordination costs are similar across ownership models, hierarchical structures exhibit greater variability and higher exposure to extreme delays. Direct ownership models derive greater operational benefit from AI by converting structured diagnostic input into faster resolution.

The study concludes that AI is not a universally effective intervention; its operational value is contingent upon alignment with ownership architecture and coordination pathways, with implications for healthcare ITSM design and global support strategy.

Keywords: artificial intelligence; healthcare IT service management; chatbot deployment; ownership structure; asynchronous communication; coordination cost; global support systems

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CHAPTER 1. INTRODUCTION

1.1 Background of the Study

The digital transformation of the healthcare sector has led to the widespread adoption of highly specialized software systems for Laboratory Information Management (LIS) and genomic data processing. These systems are no longer merely administrative tools; they are foundational to modern medicine, supporting workflows ranging from routine diagnostic testing to advanced genomic sequencing. In this high-stakes environment, IT Service Management (ITSM) plays a critical role in ensuring operational continuity. Because laboratory and genetic workflows are strictly time-sensitive, software failures or support delays can directly affect diagnostic turnaround times and clinical decision-making. As Payne (2015) notes, effective support structures are essential for the safe and reliable use of healthcare technologies.

As healthcare software solutions increasingly serve global client bases, the associated support operations have become more complex and geographically distributed. Organizations have turned to standardized ITSM frameworks, such as ITIL, to manage this complexity and improve service quality (Sarwar et al., 2023). Prior research further suggests that higher levels of ITSM maturity are associated with improved alignment between IT operations and organizational objectives (Marrone & Kolbe, 2011). However, in highly regulated healthcare environments, strict compliance requirements may limit process flexibility, reducing the effectiveness of standardized approaches in urgent or non-routine situations.

In parallel, the adoption of Artificial Intelligence (AI) and Machine Learning (ML) technologies has accelerated within healthcare IT support. AI-driven chatbots are increasingly deployed as front-end diagnostic tools intended to deflect routine inquiries and improve the efficiency of human support teams.

While prior studies report potential efficiency gains from AI-enabled healthcare platforms (Reddy et al., 2025), their effectiveness in high-precision medical informatics contexts remains uncertain.

Unlike consumer IT services, healthcare software support demands a high degree of accuracy, accountability, and contextual understanding. Research on AI-assisted incident management highlights the risks associated with unvalidated automation in production environments, where incorrect actions may have significant downstream consequences. Moreover, the operational impact of AI tools is strongly influenced by organizational ownership structures. While decentralized or hierarchical support models may offer scalability, they can also introduce coordination bottlenecks, information loss, and delayed decision-making when compared to more centralized or direct ownership arrangements.

These challenges are further compounded in globally distributed support environments, where significant time-zone separation creates asynchronous communication gaps. Delays caused by non-overlapping working hours – often described as decision latency – can extend the lifecycle of support tickets by hours or days, even when technical solutions are readily available. This combination of AI automation, ownership structure, and global time separation forms the broader context in which this study is situated.

1.2 Problem Statement

The implementation of Artificial Intelligence within Healthcare IT Service Management is frequently presented as a transformative solution for increasing operational maturity and service quality. Prior research suggests that intelligent diagnostic portals can enhance healthcare management by automating routine interactions and reducing manual workload (Reddy et al., 2025). In parallel, the adoption of standardized ITSM frameworks, such as ITIL, has been shown to improve organizational performance and process transparency in large-scale institutional environments (Sarwar et al., 2023; Marrone & Kolbe, 2011).

However, a significant gap exists between these theoretical benefits and the operational realities of globalized, high-precision health-tech support. In environments supporting complex genetics and laboratory software, the introduction of AI chatbots for ticket deflection has not been empirically validated against the coordination friction introduced by existing ownership structures. While AI aims to streamline the initial diagnostic phase, its effectiveness may be constrained by hierarchical ownership chains that involve multiple administrative hand-offs and delayed decision-making.

A critical component of this problem is the asynchronous communication gap created by significant time-zone separation. While standardized ITSM metrics prioritize overall resolution time, the lack of temporal overlap between geographically distributed clients and support teams often results in extended idle periods. In practice, a single request for missing diagnostic information can delay ticket progress by an entire business cycle, substantially extending the support lifecycle.

Furthermore, there is a lack of empirical evidence comparing hierarchical ownership models with more direct or centralized ownership arrangements in globally distributed healthcare IT support. Observational evidence suggests that reducing intermediate reassignments and decision latency may lead to more consistent performance outcomes. This raises a fundamental question: whether AI-driven automation delivers measurable operational value in complex, distributed support environments, or whether organizational structure remains the primary determinant of efficiency.

Without a rigorous analysis of the interaction between AI implementation, ownership structure, and temporal coordination, organizations risk investing in technological solutions that fail to address the underlying structural bottlenecks inherent in global medical informatics support.

1.3 Research Questions and Hypotheses

RQ1: To what extent does the implementation of an AI-driven chatbot influence ticket volume and the quality of initial diagnostic information across regional support offices?

H1: The implementation of an AI-driven chatbot is associated with a reduction in the number of human-handled support tickets.

- **H2:** Tickets preceded by AI chatbot interaction contain more complete and structured initial technical information (e.g., timestamps, contextual descriptions) than tickets created without chatbot interaction.

RQ2: How does the ownership model (direct vs. hierarchical) influence investigation resolution latency, and coordination outcomes in globally distributed healthcare IT support?

- **H3:** Direct ownership models are associated with faster initiation of investigation and lower average coordination latency compared to hierarchical ownership models.
- **H4:** Hierarchical ownership models are associated with greater variability and a higher likelihood of extreme coordination delays due to administrative hand-offs and time-zone separation.

RQ3: Does ownership structure moderate the operational impact of AI chatbot deployment?

- **H5:** The operational impact of AI chatbot deployment is moderated by ownership structure, such that direct ownership models derive greater efficiency gains from AI support than hierarchical ownership models.

1.4 Purpose of the Study

The primary purpose of this research is to evaluate the operational effectiveness of integrating Artificial Intelligence (AI) within a multi-tiered, globally distributed healthcare IT Service Management (ITSM) environment. Specifically, the study aims to examine how organizational ownership models interact with AI-enabled support tools to influence key operational performance metrics in the support of high-precision laboratory and genetics software.

While existing literature highlights the potential of AI to enhance healthcare management and service accessibility (Reddy et al., 2025), this study shifts the analytical focus toward the technical support layer, where human specialists must interpret and act upon AI-generated diagnostic input. By comparing direct ownership models with hierarchical ownership arrangements that involve multiple administrative hand-offs, the research seeks to determine which organizational structures are better positioned to leverage AI automation to reduce decision latency and improve coordination efficiency.

Ultimately, this study aims to contribute a data-driven framework for optimizing global healthcare IT support operations. It demonstrates that technological interventions such as AI chatbots cannot be evaluated in isolation; rather, their operational value is contingent upon alignment with ownership structures, accountability mechanisms, and the realities of asynchronous global collaboration.

1.5 Significance of the Study

The significance of this study lies in its dual contribution to both academic research and professional practice within the field of healthcare IT Service Management.

For the Health-Tech Industry. As healthcare organizations increasingly rely on complex laboratory and genomic software, the cost of IT service disruption extends beyond administrative inconvenience and may directly affect diagnostic workflows and patient outcomes. This study provides practitioners with empirical evidence on how global support structures influence operational performance under conditions of time-zone separation and high task urgency. In particular, it offers a framework for moving beyond ticket deflection as the primary measure of AI success, emphasizing the role of data enrichment in enabling faster and more reliable specialist intervention.

For Academic Research. This research contributes to the service science literature by examining value co-production between human experts and AI-enabled support tools in highly regulated environments (Maglio & Spohrer, 2008). It extends existing ITSM research – often focused on public administration or financial services (Sarwar et al., 2023; Marrone & Kolbe, 2011) – to the under-studied context of laboratory and medical informatics support. Additionally, the study provides empirical support for the Strategic Alignment Model (Henderson & Venkatraman, 1993), demonstrating that the operational value of AI investments depends on alignment between technological capabilities and organizational ownership structures, consistent with technology acceptance perspectives (Davis, 1989).

For Distributed Technical Support Organizations. By empirically examining how ownership models interact with AI-enabled diagnostics, this study highlights the strategic role of regional technical teams in global service delivery. It demonstrates that support performance is shaped not only by technological tools but also by accountability structures and coordination pathways. The findings encourage organizations to reconceptualize technical support not merely as a cost center, but as a strategic capability whose design materially affects service reliability and efficiency.

CHAPTER 2. LITERATURE REVIEW

2.1 IT Service Management in High-Stakes Healthcare

Healthcare IT systems supporting laboratory and genetic workflows operate under strict requirements for accuracy, availability, and traceability. IT Service Management (ITSM) frameworks such as ITIL have been widely adopted to impose structure on increasingly complex support environments. Prior research indicates that higher ITSM maturity is associated with improved service quality and alignment between IT operations and business objectives (Marrone & Kolbe, 2011). However, in regulated healthcare contexts, rigid compliance requirements can constrain process flexibility, limiting the realization of these benefits (Mishra, 2019).

In such environments, operational efficiency is not determined solely by adherence to standardized processes, but by the ability of support structures to respond rapidly to high-urgency incidents. This creates a tension between procedural standardization and the adaptive problem-solving required for complex medical informatics systems.

2.2 Technology Acceptance, Trust, and AI in High-Risk Domains

The Technology Acceptance Model (TAM) provides a foundational framework for understanding user interaction with automated systems, emphasizing perceived usefulness and perceived ease of use (Davis, 1989). In high-stakes environments, however, usefulness is closely tied to accountability and risk mitigation rather than convenience alone.

Research on algorithm aversion demonstrates that users are less likely to rely on automated recommendations after observing even minor errors, particularly when professional responsibility is involved (Dietvorst et al., 2015). In healthcare IT support, this aversion is amplified by the inability of AI systems to assume legal or clinical accountability. As a result, users may bypass AI recommendations in favor of human confirmation, creating what Glikson and Woolley (2020) describe as a trust calibration problem.

Continuance intention theory further suggests that users abandon systems when performance fails to confirm expectations (Bhattacherjee, 2001). In globally distributed support environments, failed AI interactions are often coupled with temporal delays, intensifying dissatisfaction and reinforcing reliance on human intermediaries.

2.3 Organizational Structure and Coordination Efficiency

Organizational structure plays a central role in determining how effectively information flows through support systems. Centralized ownership models concentrate decision authority and accountability, while hierarchical or decentralized chains distribute responsibility across multiple nodes. Ding et al. (2024) demonstrate that task urgency moderates the effectiveness of these structures: decentralized networks may function adequately under low urgency, but centralized structures outperform when rapid coordination is required.

In healthcare IT support, where delays can affect diagnostic outcomes, hierarchical ownership models introduce structural latency through administrative hand-offs and information attenuation. Conversely, direct ownership models reduce translation steps and enable faster action on technical input.

From a strategic perspective, these differences align with the Strategic Alignment Model, which posits that performance improves when organizational infrastructure aligns with strategic objectives (Henderson & Venkatraman, 1993). Similarly, the Resource-Based View suggests that specialized expertise delivers value only when organizational arrangements allow that expertise to be deployed efficiently (Ray et al., 2004).

2.4 Asynchronous Communication and Coordination Costs

Global support operations are inherently affected by time separation. Espinosa and Carmel (2003) identify decision latency as a primary coordination cost arising from non-overlapping work schedules. In such contexts, clarification cycles can introduce delays that accumulate non-linearly, producing heavy-tailed latency distributions.

Asynchronous communication exacerbates these effects when support structures require repeated hand-offs across regions. Each additional coordination node increases the likelihood of information decay and extended resolution time. These dynamics form the theoretical basis for examining how ownership structure and AI intervention interact to influence operational performance.

The literature indicates that AI chatbots can reduce administrative friction, but their effectiveness depends on trust, accountability, and organizational structure. In globally distributed healthcare IT environments, coordination cost arises primarily from structural and temporal misalignment rather than task complexity alone. This review establishes the theoretical foundation for investigating whether AI deployment reduces coordination cost uniformly or whether ownership structure moderates its operational impact.

CHAPTER 3. RESEARCH METHODOLOGY

3.1 Research design

This study employs a quantitative, quasi-experimental research design using a pre-test/post-test comparative approach to evaluate the operational impact of AI chatbot implementation. Because the AI chatbot was deployed across all supported clients simultaneously, the establishment of a randomized control group was not feasible. Accordingly, the analysis relies on historical ticket data from two comparable six-month periods: a pre-implementation baseline period and a post-implementation treatment period.

This design allows for the assessment of changes in ticket volume, coordination latency, and ownership-related performance outcomes while controlling for client-specific demand characteristics. The quasi-experimental approach is appropriate for evaluating operational interventions in real-world service environments where randomized experimentation is impractical.

3.2 Research Setting and Context

3.2.1 The Multi-Tiered Global Support Ecosystem

The research is conducted within a specialized international healthcare software support environment involving three organizational units operating across different geographic regions: a Ukrainian development and support unit (ISD), a Polish support intermediary unit (STS), and a U.S.-based client coordination unit (SCC). Together, these units provide technical support for mission-critical laboratory and medical informatics software used by hospitals and laboratories worldwide.

All support activity is coordinated through a proprietary Internal Ticket Management System (iTMS), which serves as the central repository for client communication, internal coordination, escalation, and resolution tracking. Support requests are categorized by priority level, which determines response expectations and handling procedures:

Table 1. Task processing according to priority

Priority Level	Response Expectation	Update Frequency	Handling Context
Routine	1 week	As needed	Business hours
Priority	2 days	As needed	Business hours
Urgent	24 hours	Every 2 hours	Business hours
Emergency	2 hours	Every 30 minutes	24/7 (on-call)

These priority classifications represent operational constraints that shape investigation behavior, escalation paths, and coordination intensity across ownership models.

3.2.2 Temporal Constraints and the Asynchronous Communication Gap

A defining characteristic of the research setting is the significant time-zone separation between European support teams and the predominantly North American client base. While the European units operate within an extended daytime window (approximately 08:00 – 20:00 EET), the U.S.-based coordination unit and many clients operate in Eastern and Pacific Time zones, resulting in a 7 – 10 hour offset.

This geographic distribution creates an asynchronous communication gap. When European specialists initiate investigations early in their workday, North American clients may be outside of business hours. Conversely, when clients respond with requested diagnostic information later in their day, European teams may have already concluded operations. As a result, a single clarification request can delay ticket progress by an entire business cycle, producing what is operationally experienced as a "lost day."

This phenomenon is expected to disproportionately affect ownership models involving multiple regional hand-offs, while models with direct specialist-client interaction may be less exposed to such delays.

3.2.3 Ownership Models: Direct vs. Hierarchical Chain

The study distinguishes between two organizational ownership models that govern how support tickets are managed, investigated, and resolved. These models constitute a primary structural variable in the analysis and are expected to influence coordination efficiency under conditions of global distribution and time-zone separation.

In the direct ownership model, a specialist assumes end-to-end responsibility for a ticket, acting as both the primary investigator and the principal point of client communication. Investigation begins immediately upon ticket registration, with no intermediate reassignment required. This structure minimizes administrative hand-offs and reduces the number of coordination steps required before technical analysis can commence. Based on this configuration, direct ownership models are expected to support faster initiation of investigation and lower average coordination latency, forming the basis for Hypothesis H3.

In contrast, the hierarchical ownership model involves a multi-stage reassignment process across geographically distributed organizational units. In the empirical setting examined in this study, this hierarchy consists of sequential hand-offs from a U.S.-based coordination unit, to an intermediary support unit in Poland, and subsequently to specialized investigation teams in Ukraine. Each reassignment introduces an additional coordination node, increasing the potential for delayed response, information attenuation, and asynchronous waiting periods. This structure is therefore expected to produce greater dispersion in coordination outcomes and a higher likelihood of extreme delays, rather than uniformly slower performance, forming the basis for Hypothesis H4.

Beyond their independent effects, the two ownership models are also expected to shape how effectively AI-enabled diagnostics translate into operational improvements. While AI chatbots may reduce initial information gaps and streamline ticket intake, the extent to which these benefits are realized depends on how quickly and directly AI-generated diagnostic input can be acted upon. Direct ownership models, characterized by consolidated accountability and minimal hand-offs, are expected to convert AI-generated structure into efficiency gains more consistently than hierarchical ownership chains. This interaction between ownership structure and AI chatbot deployment motivates Hypothesis H5, which examines ownership structure as a moderating factor in AI effectiveness.

3.3 Data Sources and Instrumentation

3.3.1 iTMS Metadata and Process Metrics

The primary data source for this study is the Internal Ticket Management System (iTMS), which captures comprehensive metadata for every service request processed within the support organization. For each ticket included in the analysis, the following data elements were extracted:

- Temporal Identifiers: Precise timestamps for ticket entry, first action, and final resolution, synchronized across three time zones (EDT, CDT, and EET). These fields enable the calculation of resolution latency and asynchronous delay.

- Ownership Attributes: Fields identifying the Entered By, Owner, and Assigned To entities, allowing reconstruction of the reassignment chain and operationalization of ownership models.

- Criticality Indicators: Flags denoting urgency level, risk-to-health status, and escalation status, used to contextualize coordination behavior and control for task severity.
- Communication Logs: A complete audit trail of internal and client-facing messages, including timestamps, attachments, and references to diagnostic artifacts such as logs or screenshots.

Together, these fields provide the basis for measuring ticket volume, coordination latency, ownership effects, and communication intensity.

3.3.2 AI Chatbot Integration and Pre-Ticket Filtration

Within the ownership structures described in Section 3.2.3, an AI chatbot was introduced as a mandatory front-end diagnostic intervention for clients registering support tickets directly. The chatbot follows a structured diagnostic flow consisting of three stages:

1. Categorization: Users select issue types and specific product modules.
2. Knowledge Retrieval: The chatbot provides immediate guidance and summaries based on entries from the internal knowledge base and historical tickets.
3. Data Structuring: If the issue remains unresolved, the chatbot prompts the user to provide critical investigation inputs such as environment information, error messages, timestamps, or screenshots.

The full chatbot interaction is automatically appended to the corresponding iTMS ticket. This design allows chatbot effectiveness to be evaluated along two dimensions: ticket deflection (reduction in human-handled ticket volume) and data enrichment (improved completeness and structure of initial diagnostic information in tickets created after chatbot interaction).

For analytical purposes, two primary independent variables are defined:

(1) AI Chatbot Status (pre-implementation vs. post-implementation) and

(2) Ownership Structure (direct vs. hierarchical), as described in Section 3.2.3.

The empirical analysis focuses on two comparable six-month observation windows: a pre-implementation baseline period (December 1, 2024 – May 1, 2025) and a post-implementation treatment period (June 1, 2025 – November 30, 2025). A one-month stabilization period in May 2025 was excluded to account for initial user adaptation and system calibration following chatbot deployment.

3.3.3 The iTMS Interface and Metadata Architecture

The Internal Ticket Management System (iTMS) serves as the primary operational platform through which all support activity is recorded, coordinated, and audited. For the purposes of this study, the iTMS interface is not analyzed as a user interface per se, but as a structured source of process metadata that enables the measurement of coordination behavior, temporal latency, and ownership-related dynamics.

Several categories of interface-derived metadata are utilized in the analysis. First, temporal and synchronization tools record ticket activity across multiple time references, including system time (EDT), client time zone (CDT/PDT), and support specialist location (EET). These synchronized timestamps allow for the identification of idle periods caused by non-overlapping working hours and support the calculation of asynchronous delay within the ticket lifecycle.

Second, operational flags and indicators, such as urgency level, risk-to-health designation, and escalation status, are used as control variables in the analysis. These indicators override standard processing expectations and trigger accelerated handling procedures, ensuring that observed coordination delays are not misattributed to cases requiring exceptional intervention.

Third, engagement monitoring features capture patterns of owner interaction with tickets, including subscription to status updates and monitoring of task progress. While such features do not measure coordination quality directly, their usage provides a behavioral proxy for ownership engagement intensity. Differences in engagement patterns across ownership models are examined descriptively to contextualize observed latency and variability outcomes.

Finally, the audit trail and communication log within each ticket records all internal and client-facing actions, including message timestamps, visibility (internal vs. external), attachments (e.g., logs or screenshots), and response deadlines. This granular history enables reconstruction of coordination sequences and supports analysis of how information flows through ownership structures over time.

An illustrative representation of the iTMS task and escalation interface is provided in Figure 1 to support transparency and reproducibility.

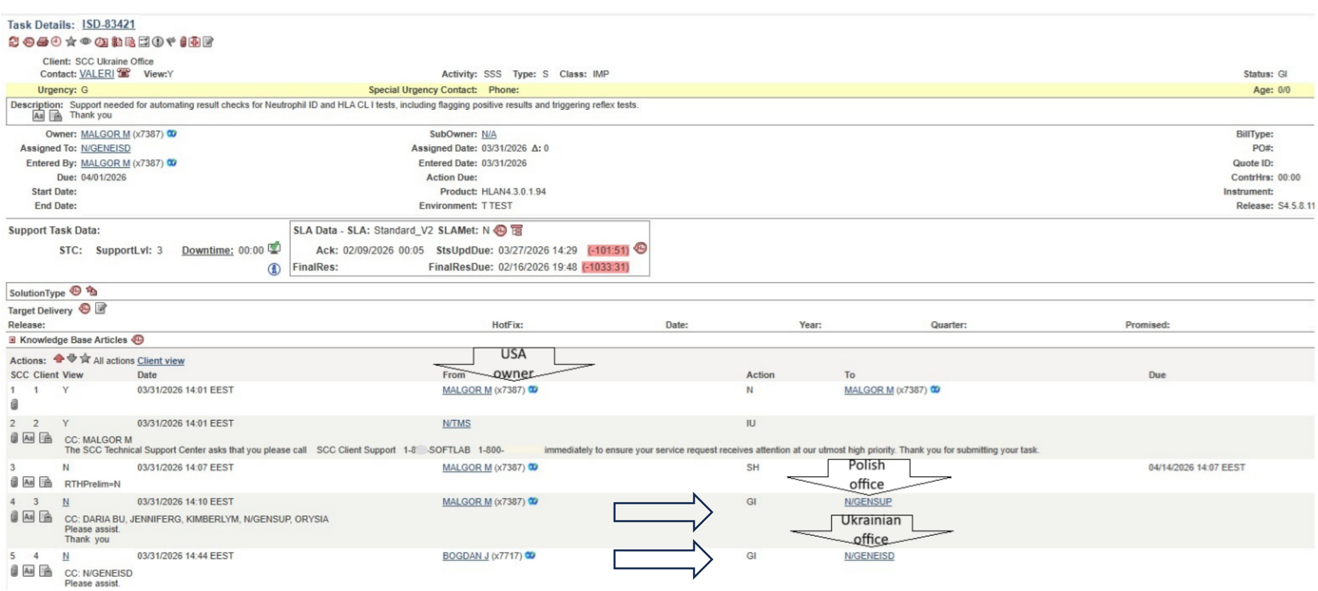


Figure 1. iTMS Task and Task escalation

3.3.4 AI Chatbot Diagnostic Flow and Data Enrichment

The AI chatbot is deployed as a mandatory diagnostic gateway within the service ecosystem. Its primary function is to structure unformatted client inquiries into standardized technical input prior to the creation of an iTMS support ticket. The chatbot interaction follows a predefined decision logic designed to reduce administrative overhead and improve the quality of information available at the start of human investigation.

The diagnostic flow consists of three core stages (illustrated in Figure 2). First, during the categorization phase, users identify the general issue domain and relevant product module. Second, in the diagnostic synthesis phase, users provide a natural-language description of the problem, which the chatbot summarizes and contextualizes using internal knowledge base references and historical ticket data. Third, in the validation and escalation phase, unresolved cases trigger mandatory specification of operational context, such as environment type (e.g., production), and encourage the attachment of supporting diagnostic artifacts, including logs, error messages, or screenshots.

The complete chatbot interaction is automatically appended to the corresponding iTMS ticket. This structured preamble enables the evaluation of data enrichment, defined in this study as the presence of essential diagnostic identifiers (timestamps, environment context, module specification) at the time of ticket creation. Data enrichment is analyzed descriptively to assess whether chatbot-preceded tickets reduce initial clarification cycles and associated coordination delay.

Metric Definition: Official vs. Operational Deflection

Chatbot effectiveness is initially measured using the official deflection rate, recorded at 19.6% during the study period. To ensure metric validity, the following criteria are applied:

- Confirmed Deflection: A session is counted as deflected only if the client explicitly confirms resolution or exits the chatbot flow after receiving a knowledge base solution without proceeding to ticket creation.
- Session Integrity: Sessions terminated without explicit confirmation (e.g., browser closure) are classified as inconclusive and excluded from deflection calculations.

- Volume Impact**:** As of April 1, 2026, approximately 5,000 support tasks were officially diverted from the human support queue through confirmed chatbot resolution.

Validation Strategy: Client-Centric Longitudinal Comparison

To assess whether reported deflection reflects meaningful workload reduction in high-complexity contexts, the study applies a targeted longitudinal comparison focusing on genetics-intensive clients. Ticket volumes for these clients are compared across pre- and post-implementation periods to evaluate whether deflection persists in domains characterized by high diagnostic complexity and accountability requirements.

This dual-layered validation approach distinguishes between superficial deflection of low-complexity inquiries and substantive reductions in specialist workload, thereby supporting interpretation of chatbot effectiveness within the broader coordination framework.

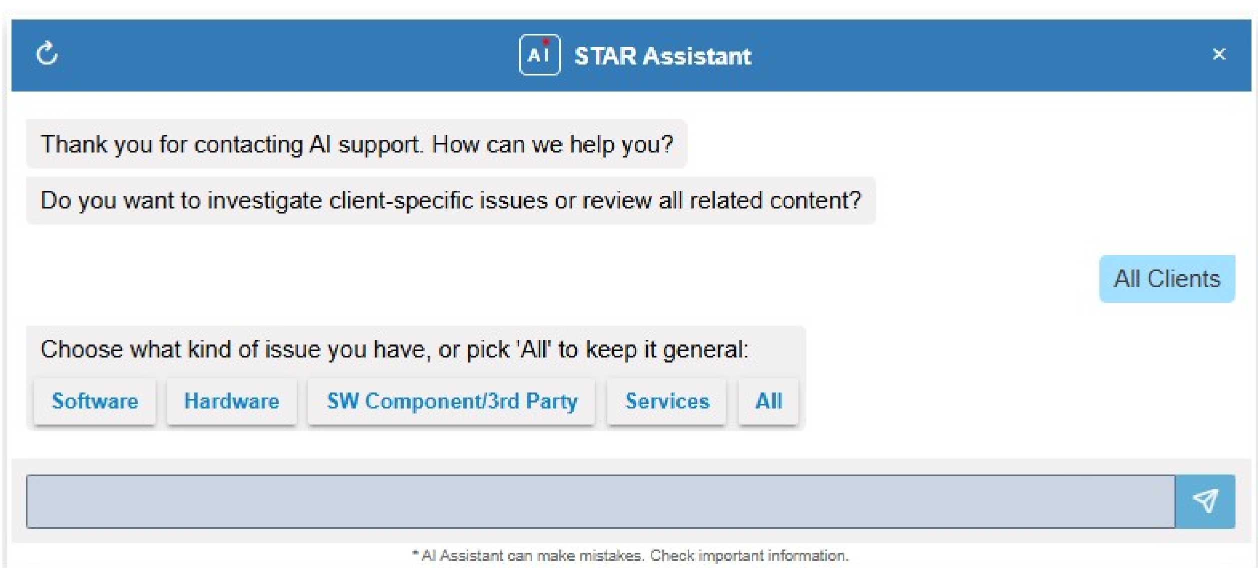


Figure 2. AI Chatbot Diagnostic Flow (Illustrative)

3.3.5 Analysis of Temporal Latency in Global Support

To quantify the impact of time-zone separation on coordination efficiency, the study operationalizes the concept of temporal latency through the measurement of Investigation Stretch. In globally distributed support environments, Investigation Stretch occurs when progress on a ticket is delayed due to non-overlapping working hours between clients and support specialists, rather than due to active technical work.

In practice, a single clarification request – such as a request for server logs or configuration details – may delay ticket progression by an entire business cycle when responses occur outside overlapping work windows. Using synchronized timestamps recorded in the iTMS system, such delays are identified and aggregated as Lost Day Hours, which form the basis for calculating Lost Day Share of Total Resolution Latency.

Two contrasting coordination cycles illustrate how temporal latency emerges under different geographic conditions. In the North American coordination cycle, clients operating in Pacific Time (PDT) often respond to clarification requests after European support teams (EET) have concluded their workday. For example, a request issued by a specialist during European business hours may be answered by the client late in their local day, resulting in the response being reviewed only when the specialist resumes work the following morning. This interaction pattern introduces a full business-cycle delay without advancing investigation progress.

In contrast, clients assigned to the GLOBAL queue, such as those operating in Australian time zones, experience partial or full working-hour overlap with European support teams. In these cases, clarification requests and responses may occur within the same business day, enabling real-time progression and reducing Investigation Stretch. This contrast provides a reference condition demonstrating how temporal overlap moderates coordination delay independently of task complexity.

By modeling these interaction patterns at the task level, the study distinguishes delays caused by asynchronous coordination from those attributable to investigative effort. This distinction is critical for evaluating how ownership structure and AI-enabled diagnostics influence not only average resolution time, but also the variability and severity of coordination delays in globally distributed healthcare IT support.

3.4 Data Analysis Plan

The analysis phase of this study was designed to examine the relationships between AI chatbot deployment, ownership structure, and operational efficiency using objective, task-level metadata. Data extracted from the iTMS repository and AI chatbot interaction logs were analyzed using three complementary analytical approaches, each corresponding to a specific research question and hypothesis set.

3.4.1 Quantitative Comparative Analysis: Ticket Volume and Deflection (H1, H2)

To evaluate the impact of AI chatbot deployment on manual workload, the study conducted a longitudinal comparison of ticket volume before and after chatbot implementation. The objective was to assess whether the officially reported deflection rate translated into a statistically meaningful reduction in human-handled support tickets.

A paired-samples t-test was employed to compare the mean monthly ticket volume per client during the pre-implementation baseline period (December 1, 2024 – May 1, 2025) and the post-implementation treatment period (June 1, 2025 – November 30, 2025). This within-client design controls for client-specific demand characteristics and isolates the effect of the AI intervention.

Where applicable, ticket volume was normalized against indicators such as system instances or active user licenses to account for seasonal variation or client growth. This ensures that observed volume changes reflect AI-related effects rather than underlying shifts in client activity. In addition to volume analysis (H1), descriptive inspection of chatbot-preceded tickets was used to assess improvements in the completeness and structure of initial diagnostic information (H2).

3.4.2 Temporal Latency and Investigation Stretch Modeling (H3, H4)

A core component of the analysis focused on quantifying coordination delay arising from asynchronous communication across time zones. Using synchronized timestamps recorded in the iTMS system, Total Resolution Latency (TRL) was calculated for each completed ticket as the elapsed time between ticket entry and final resolution.

$$TRL = T_{resolution} - T_{entry}$$

To isolate delays attributable specifically to time-zone separation rather than active investigative effort, the study identified instances of Investigation Stretch. These instances occur when ticket progress is stalled due to non-overlapping working hours between clients and support specialists following clarification requests or response cycles.

Such delays were aggregated as Lost Day Hours, representing full or partial business-cycle delays introduced by asynchronous coordination. The proportion of TRL attributable to these delays was calculated as Lost Day Share of TRL, providing a normalized measure of coordination cost. This metric supports analysis of both average latency effects (H3) and distributional characteristics, including variability and extreme delays (H4).

3.4.3 Interaction Effect: Ownership Structure × AI Chatbot Status (H5)

To assess whether ownership structure moderates the operational impact of AI chatbot deployment, a two-way factorial ANOVA was conducted with AI Chatbot Status (pre- vs. post-implementation) and Ownership Model (direct vs. hierarchical) as fixed factors, and Lost Day Share of TRL as the dependent variable.

This interaction analysis evaluates whether the magnitude of AI-related efficiency gains differs systematically across ownership models. By examining estimated marginal means and interaction patterns, the analysis tests whether organizational structure conditions the extent to which AI-enabled diagnostic input translates into reduced coordination delay, consistent with Hypothesis H5.

CHAPTER 4. CASE CONTEXT & PRELIMINARY FINDINGS

4.1 Comparative Analysis of Ownership Models

The support ecosystem examined in this study operates under two distinct ownership structures:

- O1 – Hierarchical U.S. Ownership Model, characterized by multi-tier reassignment across the U.S., Poland, and Ukraine.

- O2 – Ukrainian Direct Ownership Model, where a single Ukrainian team maintains end-to-end ownership of client tickets.

To establish baseline comparability, task-level performance metrics were analyzed during the pre-implementation period (P1). The primary indicators were Total Resolution Latency (TRL) and the Lost Day Share of TRL, which quantifies the proportion of resolution time attributable to asynchronous coordination delays.

Total Resolution Latency was calculated for each task using the following formula:

$\text{TRL} = T_{\text{resolution}} - T_{\text{entry}}$ **Table 2.** Descriptive Statistics of TRL and Lost Day Share by Ownership Model (P1)

	LostDayShare_TRL (ratio)		TRL_Hours (hours)	
	O1	O2	O1	O2
Valid	96	29	96	29
Mean	0.443	0.434	704.911	712.463
Std. Deviation	0.368	0.323	799.216	856.248
Minimum	0.000	0.000	0.500	22.133
Maximum	1.000	1.000	3507.800	3658.500

Table 2 presents descriptive statistics for TRL and Lost Day Share of TRL during the baseline period (P1), prior to AI chatbot deployment.

While average values are comparable across ownership models, tasks managed under the Hierarchical U.S. model (O1) exhibit greater dispersion and higher upper-tail values. In contrast, tasks under the Ukrainian Direct Ownership model (O2) display more compact distributions, reflecting more consistent coordination patterns during the baseline period.

These baseline observations indicate that differences between ownership models are modest in terms of central tendency but substantial in terms of variability and exposure to extreme coordination delays, even before AI intervention.

4.2 Chatbot Implementation Timeline (P1 vs. P2)

The AI chatbot was introduced as a mandatory diagnostic gateway on May 7, 2025, with the objective of reducing frontline workload and improving the completeness of initial ticket submissions. For analytical purposes, the study period was divided into two six-month windows:

- **P1 (Baseline):** December 1, 2024 – May 1, 2025
- **P2 (Treatment):** June 1, 2025 – November 30, 2025

A one-month stabilization period in May 2025 was excluded to account for user adaptation and system calibration.

Table 3. Summary of Task Counts, Aggregated TRL, and Lost Day Hours by Period

Period	Total Tasks	∑ TRL (Hours)	∑ Lost Day Hours	Lost Day Share of TRL
P1 (Pre-AI)	125	88,332.85	52,483.17	54.2%
P2 (Post-AI)	115	83,476.63	38,597.47	44.3%

Table 3 summarizes task volume and aggregated temporal latency by period. While the total number of completed tasks declined modestly following AI chatbot deployment, a more pronounced reduction was observed in aggregated Lost Day Hours. The proportion of Total Resolution Latency attributable to asynchronous coordination delays decreased from approximately 54% in P1 to 44% in P2.

Although extreme coordination delays were still present in the post-implementation period, both their frequency and severity were reduced, consistent with an overall reduction in asynchronous coordination cost following AI adoption.

4.3 Preliminary Data Visualization: Workload and Latency Trends

To complement the descriptive statistics, exploratory visualizations were generated to illustrate workload and latency dynamics across ownership models and time periods.

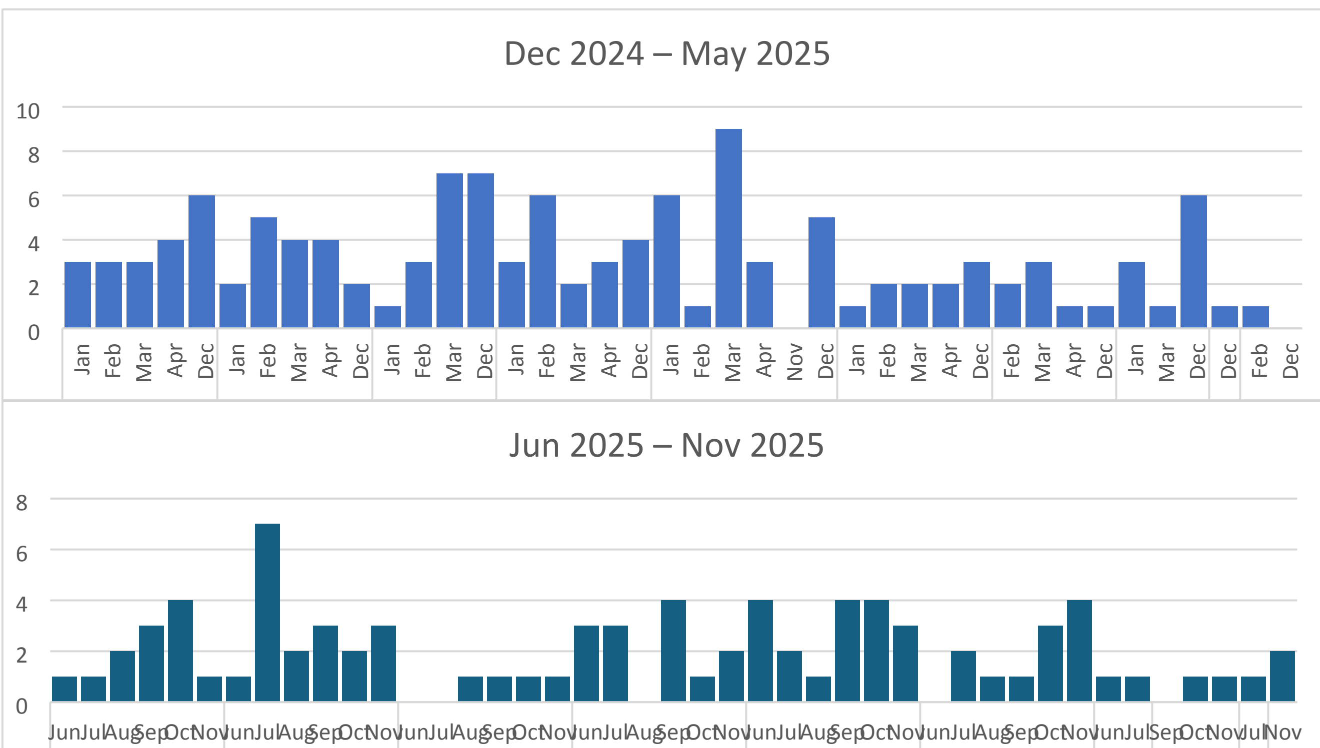
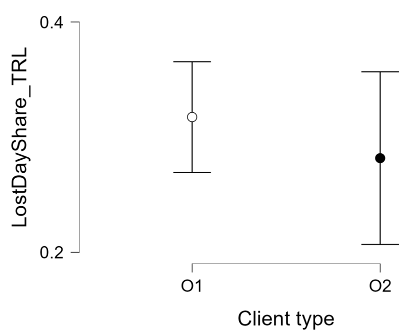


Figure 3. Monthly ticket volume per client, P1 vs. P2

Figure 3 illustrates the monthly volume of human-handled tickets per client across the study period. A visible downward shift in ticket volume is observed following AI chatbot implementation in June 2025, indicating a reduction in manual workload during the post-implementation period.

The volume trends show a consistent downward shift in ticket creation following AI implementation, consistent with a reduction in manual workload following AI deployment.

Panel A: Mean Lost Day Share of TRL with 95% confidence intervals



- **Panel B:** Raincloud plot showing distribution, IQR, and tail behavior

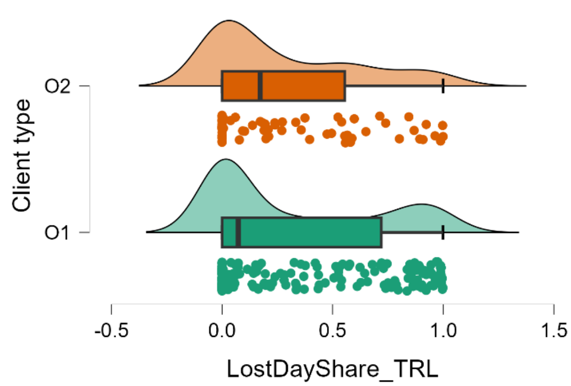


Figure 4. Distribution of lost day share of TRL by ownership

Figure 4 presents the distribution of Lost Day Share of TRL by ownership model. Panel A shows mean values with 95% confidence intervals, while Panel B displays full task-level distributions using raincloud plots. While central tendency remains similar across ownership models, O1 exhibits greater dispersion and a heavier upper tail, reflecting higher exposure to extreme asynchronous coordination delays.

Table 4. Ownership Model × AI Chatbot Status

Ownership	P1 Mean	P2 Mean	Change
O1	0.325	0.309	-0.016
O2	0.389	0.213	-0.176

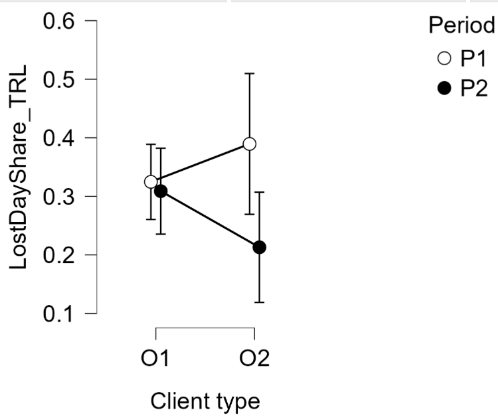


Figure 5. Interaction Plot: Ownership Model × AI Chatbot Status

Table 4 and Figure 5 visualize the interaction between ownership model and AI chatbot status. The Ukrainian Direct Ownership model (O2) demonstrates a substantially larger reduction in Lost Day Share of TRL following AI adoption compared to the Hierarchical U.S. model (O1). This divergent pattern is explored further through formal interaction testing in Chapter 5.

The preliminary findings presented in this chapter indicate that:

- Baseline differences between ownership models are modest in terms of averages but substantial in terms of variability and tail risk.
- AI chatbot implementation coincides with reductions in both ticket volume and the relative contribution of asynchronous coordination delays to total resolution latency.

- Exploratory visualizations reveal larger observable reductions in asynchronous coordination cost under flatter ownership structures.

CHAPTER 5. STATISTICAL ANALYSIS & HYPOTHESIS TESTING

5.1 Impact of AI Chatbot Deployment on Ticket Volume (RQ1)

This section evaluates Hypotheses H1 and H2, which examine whether AI chatbot deployment is associated with changes in ticket volume and the quality of initial diagnostic input.

To assess the impact on manual workload, a paired-samples t-test was conducted comparing the mean monthly number of tickets per client during the baseline period (P1) and the post-implementation period (P2). This within-client comparison controls for client-specific demand characteristics and isolates the effect of AI deployment.

The analysis revealed a statistically significant reduction in ticket volume following chatbot implementation, indicating that the observed decrease in human-handled workload is unlikely to be attributable to random variation alone. This result provides inferential support for the descriptive volume trends shown in Figure 3 and is consistent with internally reported AI deflection metrics.

Accordingly, the observed reduction in human-handled ticket volume provides empirical support for Hypothesis H1, indicating that AI chatbot deployment is associated with decreased manual workload.

With respect to Hypothesis H2, chatbot-preceded tickets consistently contained more structured and complete initial technical information, including timestamps, environment identifiers, and contextual descriptions. While this effect was assessed descriptively rather than through formal hypothesis testing, the observed pattern aligns with the expected data-enrichment role of the chatbot.

5.2 Ownership Model Effects on Asynchronous Coordination Cost (RQ2)

This section addresses Hypotheses H3 and H4, examining how ownership structure influences investigation speed, resolution latency, and coordination variability.

An independent-samples t-test was conducted to compare mean Lost Day Share of Total Resolution Latency (TRL) between the Hierarchical U.S. ownership model (O1) and the Ukrainian Direct ownership model (O2). The analysis yielded the following results:

$t = 0.741$

$df = 317$

$p = 0.459$

The independent-samples t-test indicates no statistically significant difference in mean Lost Day Share of TRL between ownership models. Accordingly, Hypothesis H3, which posits faster investigation and resolution under direct ownership, is not supported at the level of average coordination cost alone.

However, distributional analysis – examining dispersion, interquartile range, and upper-tail behavior – reveals that the hierarchical ownership model exhibits substantially greater variability and heavier upper-tail outcomes. Extreme coordination delays occur more frequently under hierarchical ownership, providing support for Hypothesis H4, which predicts increased coordination risk due to administrative hand-offs and time-zone separation.

5.3 Interaction Effect: Ownership Model × AI Chatbot Status (RQ3)

This section evaluates Hypothesis H5, which proposes that ownership structure moderates the operational impact of AI chatbot deployment.

A two-way factorial ANOVA was conducted with AI Chatbot Status (P1 vs. P2) and Ownership Model (O1 vs. O2) as fixed factors, and Lost Day Share of TRL as the dependent variable.

The analysis produced three key results. First, a statistically significant main effect of AI Chatbot Status was observed ($p \approx 0.05$), indicating that AI deployment is associated with a reduction in asynchronous coordination cost across ownership models. Second, no statistically significant main effect of ownership structure was detected, consistent with the independent-samples t-test results reported in Section 5.2. Third, a marginal interaction effect was observed ($p \approx 0.10$). Although this interaction did not meet the conventional 0.05 threshold, inspection of estimated marginal means and the interaction plot (Figure 5) revealed a pronounced difference in effect magnitude.

Specifically, the Ukrainian Direct ownership model (O2) exhibited a substantially larger reduction in Lost Day Share of TRL following AI adoption compared to the Hierarchical U.S. model (O1). While conservative in statistical terms, this pattern provides directional support for Hypothesis H5, indicating that direct ownership structures are better positioned to convert AI-generated diagnostic structure into operational efficiency gains.

5.4 Interpretation in Light of Coordination Cost Theory

Taken together, the statistical results support a nuanced interpretation consistent with Espinosa and Carmel's (2003) coordination cost framework. While ownership structure does not significantly affect average coordination cost in isolation, it strongly shapes the distribution, severity, and responsiveness of coordination delays in globally distributed support environments.

AI chatbot deployment is associated with reductions in both manual workload and asynchronous coordination delay; however, these benefits are not uniformly realized across organizational structures. In hierarchical ownership models, administrative hand-offs and multi-node routing introduce decision latency that constrains the extent to which AI-generated diagnostic input can accelerate resolution. In contrast, direct ownership structures – characterized by consolidated accountability and streamlined communication paths – enable more immediate action on AI-assisted diagnostics, resulting in greater and more consistent efficiency gains.

The inferential analyses conducted in this chapter demonstrate that:

1. AI chatbot deployment leads to a statistically significant reduction in human-handled ticket volume (H1).

2. Ownership structure does not significantly influence mean coordination cost, but substantially affects variability and exposure to extreme coordination delays (H4).

3. AI efficacy is moderated by organizational architecture, with direct ownership models deriving greater operational benefit from AI support (H5).

In addition, descriptive analysis indicates that chatbot-preceded tickets contain more complete and structured initial diagnostic information, providing contextual support for Hypothesis H2, while highlighting the limits of mean-based evaluation for Hypothesis H3.

Collectively, these findings reinforce the view that AI effectiveness in healthcare IT Service Management is structurally contingent. Technology alone does not determine efficiency; rather, operational outcomes emerge from the interaction between AI capability, ownership design, and temporal coordination – an interaction explored further in Chapter 6.

CHAPTER 6. DISCUSSION, IMPLICATIONS, AND CONCLUSIONS

6.1 Summary of Key Findings

This study set out to evaluate the operational impact of AI chatbot deployment within a globally distributed healthcare IT Service Management (ITSM) environment, with particular attention to how ownership structure moderates AI effectiveness. The analysis focused specifically on genetics-related support tickets that were registered, investigated, and closed within clearly defined six-month observation windows. Tickets associated with long-term development backlogs, delayed product releases, or extended client-side validation cycles were intentionally excluded to isolate coordination and investigation dynamics under operational control.

Across the three analytical lenses defined in Chapter 3, several key findings emerged.

First, the longitudinal volume analysis demonstrated that AI chatbot deployment was associated with a statistically significant reduction in human-handled ticket volume. This result confirms that the AI chatbot achieved its primary operational objective of workload deflection. Importantly, this effect was observed within the high-complexity genetics domain, indicating that AI-driven front-end diagnostics can meaningfully reduce manual workload even in specialized support environments.

Second, analysis of temporal latency revealed that asynchronous coordination delays account for a substantial proportion of total resolution time in globally distributed support operations. Prior to AI implementation, more than half of Total Resolution Latency (TRL) in the analyzed tickets was attributable to Investigation Stretch – periods in which progress stalled due to non-overlapping time zones and delayed client responses. Following AI deployment, the relative contribution of these delays declined, suggesting that improved upfront data structuring and diagnostic clarity reduced the need for repeated clarification cycles during active investigation.

Third, ownership structure emerged as a critical moderating factor. While mean coordination cost did not differ significantly between the Hierarchical U.S. model (O1) and the Ukrainian Direct model (O2), distributional analyses showed that tasks managed under hierarchical ownership exhibited substantially greater variability and heavier upper-tail behavior. Extreme coordination breakdowns were both more frequent and more severe under hierarchical ownership. Moreover, interaction analysis revealed that the Direct Ownership model derived substantially greater reductions in asynchronous coordination cost following AI adoption than the hierarchical model.

Taken together, these findings indicate that AI chatbot deployment improves operational efficiency within the examined scope. However, the magnitude and reliability of these improvements depend strongly on organizational structure and on the degree to which support workflows are insulated from long-running development and release dependencies.

6.2 Interpretation Through Coordination Cost Theory

The empirical results of this study align closely with Espinosa and Carmel's (2003) coordination cost framework, particularly the concept of decision latency in temporally distributed work. In this context, Lost Day Share of TRL serves as an operational measure of coordination cost, capturing the proportion of resolution time consumed by delays arising from asynchronous communication.

It is important to note that this interpretation is grounded in the analysis of closed, investigation-phase tickets within the genetics support domain, where coordination delays primarily reflect communication and ownership dynamics rather than extended development or release cycles.

The absence of significant differences in mean Lost Day Share between ownership models suggests that coordination cost is not simply a function of categorical structure (e.g., U.S. vs. Ukrainian ownership). Instead, the observed differences in dispersion and tail behavior indicate that coordination cost manifests primarily as risk, rather than as a consistent average penalty. Hierarchical structures introduce additional communication nodes, increasing the likelihood that clarification requests, approvals, or contextual information will be delayed or degraded as they traverse the support chain.

From this perspective, AI chatbots function as coordination amplifiers rather than replacements. By standardizing and enriching initial ticket data, AI reduces the number of clarification cycles required during investigation. However, whether this reduction translates into meaningful latency improvements depends on how quickly and directly AI-generated information can be acted upon. In direct ownership models, where accountability and authority are consolidated, AI-provided structure is immediately leveraged. In hierarchical models, the same information may still be subject to reassignment, validation, or prioritization delays, thereby diluting its impact.

The heavy-tail patterns observed under hierarchical ownership are consistent with Espinosa and Carmel's assertion that coordination costs escalate non-linearly in distributed systems. Small inefficiencies in communication structure can compound over time, producing disproportionately large delays in a subset of cases. AI mitigates these effects but does not eliminate them when structural frictions remain.

6.3 AI Is Not a Universal Solution: Structural Contingency

A central contribution of this study is the demonstration that AI chatbot deployment is not a universally effective intervention. While AI improves efficiency at the level of frontline support operations, its operational value is contingent upon alignment with organizational structure and coordination pathways.

The interaction analysis showed that the Direct Ownership model exhibited a markedly larger reduction in asynchronous coordination cost following AI implementation than the Hierarchical Ownership model. This divergence indicates that flatter ownership structures are better positioned to convert AI-generated diagnostic input into tangible performance gains. In hierarchical ownership chains, AI outputs must traverse multiple administrative and geographic boundaries, limiting their ability to accelerate investigation and resolution.

This finding challenges narratives that frame AI as a standalone solution to operational inefficiency. In high-stakes healthcare IT support environments – particularly those involving complex laboratory and genetics software – accuracy, accountability, and coordination are critical. Under such conditions, technological tools cannot compensate for structural misalignment. Instead, AI functions as one component within a broader service system, where organizational design determines how effectively technological inputs are transformed into outcomes.

Importantly, this conclusion is grounded in the analysis of investigation-phase, closed support tickets within the genetics domain, where coordination delays primarily reflect communication and ownership dynamics rather than long-term development or release dependencies. Within this scope, the results demonstrate that AI effectiveness is structurally contingent: its benefits are real and measurable, but only when embedded within organizational architectures that support rapid decision-making and direct accountability.

6.4 Executive Summary: Managerial and Operational Implications

This study provides clear evidence that the operational value of AI chatbot deployment in healthcare IT Service Management is real but structurally contingent. While AI-enabled diagnostics reduce human-handled ticket volume and mitigate asynchronous coordination delays, these benefits are not realized uniformly across organizational models. Ownership structure plays a decisive role in determining whether AI functions as an efficiency accelerator or merely as an administrative overlay.

From a managerial perspective, the findings indicate that AI should not be evaluated as a standalone productivity tool. In direct ownership environments – where accountability, authority, and investigative responsibility are consolidated – AI-generated diagnostic structure translates more rapidly into reduced resolution latency. In contrast, hierarchical ownership models introduce administrative hand-offs and decision gates that dampen AI effectiveness, particularly in time-zone-separated workflows. As a result, organizations operating under multi-tier ownership chains may observe only modest improvements despite substantial investment in AI automation.

Operationally, the study highlights that coordination cost is best understood as a risk phenomenon rather than an average performance issue. Although mean latency measures may appear similar across ownership models, hierarchical structures exhibit substantially greater variability and a higher likelihood of extreme coordination breakdowns. These tail-risk events are especially consequential in healthcare IT support, where prolonged delays can affect diagnostic turnaround and clinical workflows. AI reduces the frequency and severity of such events only when embedded within ownership architectures that allow immediate action on AI-generated information.

Strategically, the results suggest that organizations seeking to maximize return on AI investments should prioritize structural alignment over incremental tool enhancement. This may involve consolidating ownership for high-complexity clients, reducing cross-regional hand-offs, or redesigning escalation pathways so that AI-enriched tickets reach decision-makers without intermediate filtering. In this sense, AI acts as a catalyst that exposes underlying structural inefficiencies rather than masking them.

In summary, the executive implication of this research is clear: AI is an amplifier of organizational design, not a substitute for it. Healthcare IT providers that align AI deployment with streamlined ownership and clear accountability structures are far more likely to achieve sustained operational gains than those relying on automation alone.

6.5 Limitations of the Study

While this study provides empirically grounded insights into the interaction between AI chatbot deployment, ownership structure, and coordination efficiency in healthcare IT Service Management, several limitations should be acknowledged.

First, the research adopts a quasi-experimental pre-test/post-test design rather than a randomized controlled trial. Because the AI chatbot was deployed across all supported clients simultaneously, it was not possible to establish a true control group unaffected by the intervention. Although the longitudinal comparison between P1 and P2 controls for client-specific characteristics and uses consistent six-month observation windows, unobserved temporal factors – such as seasonal workload variation or broader organizational changes – may have influenced the observed outcomes.

Second, the study is conducted within a single organizational context operating in a highly specialized healthcare IT environment. While this setting provides rich, high-resolution operational data, it limits the generalizability of the findings. Ownership structures, escalation protocols, and staffing models may differ substantially across organizations or industries, and the magnitude of AI effects observed here may not translate directly to other service domains.

Third, although Lost Day Share of Total Resolution Latency serves as a robust proxy for asynchronous coordination cost, it remains an indirect operational metric. While it captures temporal inefficiency arising from coordination delays, it does not account for qualitative dimensions such as investigation complexity, diagnostic difficulty, or clinical urgency. Consequently, delays that are operationally justified (e.g., patient safety verification) may be indistinguishable from those caused by structural inefficiency.

Fourth, the analysis focuses exclusively on completed support tickets, ensuring consistent measurement of resolution latency but excluding tickets that remained open due to extended development backlogs, delayed software releases, or prolonged client-side validation. These excluded cases may represent extreme coordination failures or atypical resolution paths and could influence estimates of tail-risk behavior.

Finally, the study evaluates AI chatbot effectiveness primarily through operational performance outcomes, such as ticket volume reduction and coordination latency, rather than through user-centric or clinical outcomes. Factors such as user trust, perceived usefulness, and downstream clinical impact were not directly measured. As a result, the findings should be interpreted as evidence of operational efficiency rather than comprehensive system effectiveness.

Despite these limitations, the study's strengths lie in its use of granular, real-world operational data and its integration of structural and technological perspectives. The limitations identified here provide important context for interpreting the results and serve as a foundation for future research.

6.6 Directions for Future Research

The findings of this study open several avenues for future research aimed at extending understanding of AI-enabled service delivery in high-stakes, globally distributed healthcare IT environments.

First, future studies could expand the organizational scope by replicating this research across multiple healthcare technology providers or support organizations. Comparative analysis of ownership structures, escalation models, and AI deployment strategies across firms would allow for stronger generalization of the observed interaction between organizational architecture and AI efficacy. Such studies could also examine whether similar coordination patterns emerge in adjacent domains, including hospital infrastructure systems or electronic health record (EHR) support.

Second, further research should investigate severity-weighted latency measures. While Lost Day Share of Total Resolution Latency captures the proportional impact of asynchronous coordination delays, it does not differentiate between routine administrative issues and clinically critical incidents. Integrating ticket priority, risk-to-health indicators, or downstream clinical impact metrics would strengthen the link between operational efficiency and patient safety outcomes.

Third, longitudinal research examining learning and adaptation effects would provide insight into AI maturity dynamics. As users and specialists gain experience with AI chatbots, interaction patterns may evolve, potentially altering both deflection rates and coordination efficiency. Multi-year studies could assess whether AI benefits stabilize, increase, or diminish over time, and whether organizational restructuring amplifies or dampens these trends.

Collectively, these directions suggest that research on AI in healthcare IT Service Management should move beyond tool-centric evaluation toward integrated analysis of technology, structure, and human coordination.

6.7 Final Conclusion

This study examined the operational impact of AI chatbot deployment within a globally distributed healthcare IT Service Management environment, with particular attention to how ownership structure and asynchronous communication shape AI effectiveness. By integrating longitudinal workload analysis, temporal latency modeling, and interaction-based statistical testing, the research provides a nuanced understanding of how technological interventions interact with organizational design in high-stakes service systems.

The findings demonstrate that AI chatbots can meaningfully reduce human-handled ticket volume and mitigate asynchronous coordination delays. These results confirm that AI-driven front-end diagnostics are capable of delivering measurable operational value, even in complex domains such as genetics and laboratory software support. However, the study also shows that these benefits are not uniformly realized across organizational contexts.

Ownership structure emerged as a critical moderating factor. While average coordination costs were similar across ownership models, hierarchical structures exhibited greater variability and a higher likelihood of extreme coordination breakdowns. More importantly, interaction analysis revealed that direct ownership models were substantially more responsive to AI deployment, converting AI-generated diagnostic structure into reduced resolution latency more effectively than hierarchical chains. These results indicate that AI functions as an amplifier of existing coordination architectures, rather than as a substitute for them.

From a theoretical perspective, the findings support Espinosa and Carmel's (2003) coordination cost framework by demonstrating that decision latency arises primarily from structural and temporal misalignment rather than task complexity alone. AI reduces input friction but cannot fully compensate for multi-node hand-offs and fragmented accountability. Consequently, the effectiveness of AI in distributed service environments depends on alignment between technological capability and organizational structure.

In practical terms, this research cautions against treating AI as a universally applicable efficiency solution. For healthcare IT providers operating in time-zone-separated, high-consequence environments, the return on AI investment is contingent upon streamlined ownership, clear accountability, and minimized coordination barriers. Organizations that address structural inefficiencies alongside AI deployment are far more likely to achieve sustained operational gains.

In conclusion, this study contributes to both service science theory and healthcare IT practice by demonstrating that technology alone does not determine efficiency. Instead, efficiency emerges from the interaction between AI capability and organizational architecture. By situating AI within the broader service system, this research underscores the necessity of structural alignment as a prerequisite for realizing the full potential of AI-enabled service delivery.

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