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DESIGN AND IMPLEMENTATION OF AN AI-BASED DECISION SUPPORT SYSTEM FOR IT SUPPORT UNITS

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ABSTRACT

Artificial Intelligence (AI) is a key driver of digital transformation in organizational processes. When integrated into Decision Support Systems (DSS), it enables faster, data-driven, and more consistent decision-making, especially in operational settings such as IT support units. This study presents the design and implementation of an AI-powered DSS that combines a Natural Language Processing (NLP)–based chatbot with structured data analytics to improve problem resolution, reduce human workload, and generate managerial insights. The system was implemented as a modular web application using the ASP.NET Core MVC framework. A chatbot interface interacts with users in natural language, processes queries through OpenAI's language-model API, and records sessions in a Microsoft SQL Server database. At the end of each support session, users provide feedback, and the system can generate an automatic summary of the solution process. Administrators access these records through a dashboard that presents analytical visualizations, frequently encountered problems, and performance indicators for chatbot-assisted resolutions. A scenario-based simulation with 50 typical IT support cases was conducted to evaluate the system. Results showed that 88% of responses were considered helpful, while the average time-to-first-suggestion was 1.68 ± 0.21 seconds (client side). AI-generated summaries were also evaluated by human reviewers (Cohen's $\kappa = 0.87$) and found to be coherent and contextually accurate. These findings indicate that AI-integrated DSS architectures can enhance user satisfaction, reduce response time, and support organizational learning by transforming tacit problem-solving interactions into analyzable knowledge assets.

Keywords: Artificial intelligence, decision support systems, natural language processing, chatbots, IT helpdesk automation, organizational learning.

1 INTRODUCTION

Organizations increasingly rely on data-driven approaches as workflows grow in complexity and digital interactions proliferate. In this context, Artificial Intelligence (AI)—systems that learn, reason, and solve problems—has become a transformative enabler for efficiency, workload reduction, and consistent decision quality [8]. Among prominent applications, Decision Support Systems (DSS) leverage data and analytical models to assist decision-makers in unstructured or semi-structured problems; when coupled with AI, DSS can reduce uncertainty and support complex tasks in data-intensive domains. Beyond automating answers, contemporary helpdesk chatbots are increasingly expected to capture and structure knowledge for organizational reuse; our architecture explicitly targets this goal via a unified data pipeline [16].

A priority domain for AI-powered DSS is IT support. Successful adoption in such settings is socio-technical: beyond technical readiness, organizations need managerial support, employee training, and clear role communication [5]; insufficient transparency and explainability can erode trust and engagement [7].

This study presents a web-based, AI-powered DSS for institutional IT helpdesks. The system combines an NLP-based chatbot for real-time assistance with structured logging of interaction artefacts in SQL Server, and an administrator-oriented analytics dashboard for monitoring frequent issues, evaluating performance, and informing strategic action. The implementation uses ASP.NET Core MVC and integrates OpenAI's language-model API for natural-language input/output.

We detail the theoretical grounding, technical design, and simulation-based assessment of the architecture. Beyond technical efficacy, we highlight the system's potential to support institutional knowledge management, foster user trust, and integrate AI tools into structured organizational processes, consistent with recent findings [1], [6].

Our contribution is positioned as a hybrid DSS with Intelligent DSS characteristics, coupling an NLP chatbot with a structured analytics pipeline to institutionalize troubleshooting knowledge and support managerial decision-making [9], [10], [16]. We also adopt a metrics-first evaluation stance with client-side latency and κ-based summary reliability to ensure transparent reporting from the outset [13], [17].

1.1 Literature Review

Recent studies emphasize the transformative impact of Artificial Intelligence (AI) on organizational decision-making, knowledge dissemination, and user experience. Integrating AI into decision support systems (DSS) has been shown to enhance operational efficiency, support faster and more reliable data-driven decisions, and significantly mitigate decision ambiguity compared with traditional models [7], [8]. However, as noted by Chowdhury et al. [1], prioritizing transparency and explainability in AI system design is crucial for fostering managerial trust and long-term acceptance within organizations.

AI–human collaboration models have also gained considerable attention for their role in increasing organizational agility and productivity. Chowdhury et al. [1] underline that fostering knowledge-sharing and trust in AI systems can lead to significant improvements in employee efficiency and overall business performance. Moreover, Natural Language Processing (NLP) technologies have emerged as essential components of chatbot applications, enabling real-time interaction, contextual understanding, and adaptive response generation. Madhumita et al. [2] emphasize the transformative role of AI technologies in performance management through contextual interaction and real-time feedback, while Casillo et al. [3] highlight the critical importance of context-aware knowledge handling and instantaneous interactions provided by chatbots, especially in structured training environments. Such chatbot capabilities are most impactful when embedded into a DSS pipeline that logs client-side timings and user feedback for transparent evaluation [13], [17].

Furthermore, the literature identifies the integration of AI not merely as a technical challenge but as a comprehensive socio-technical transformation requiring human skills, collaboration, and organizational readiness. As highlighted by Zirar et al. [5], successful AI implementation within the workplace necessitates not only technological infrastructure but also continuous collaboration, human capability development, and robust organizational preparedness. Recent research stresses that effective adoption of AI relies heavily on transparent expectation management, ethical stewardship—including privacy protection, bias mitigation, and trust cultivation—as well as the strategic alignment of AI initiatives with existing business workflows and strategies. Lee et al. [6] particularly emphasize the importance of aligning AI initiatives strategically to enhance organizational processes, while Romero-Gómez et al. [7] underline ethical governance and transparency as pivotal factors to secure employee trust and long-term organizational sustainability.

Systematic reviews on agent-based chatbot technologies by Calvaresi et al. [4] underline their advantages in flexible conversation management, adaptive response handling, and context-aware capabilities. Such features are critical in dynamic support and decision-making contexts, such as IT helpdesk operations, making them particularly valuable in modern organizational environments.

We position our system within classical DSS taxonomies—model-driven, data-driven, and knowledge-driven—underscoring its hybrid nature, as discussed by Turban et al. [9]. Practically, the chatbot mediates knowledge capture, analytics quantify outcomes (e.g., Time-to-Resolution (TTR)), and stored cases enhance decision quality. Owing to its NLP, retrieval, and summarization capabilities, the system also exhibits Intelligent DSS (IDSS) characteristics, consistent with Turban et al. [10]. This framing differentiates our work from prior helpdesk chatbots by emphasizing the institutionalization of knowledge and a metrics-driven analytics pipeline. Aligned with these insights, the proposed system integrates an NLP-powered chatbot, structured data management, and an administrator-oriented analytics dashboard to enhance IT-support efficiency, ensure effective knowledge retention, and foster continuous organizational learning.

Recent surveys on LLM-based chatbots emphasize human-centric and transparent evaluation protocols [13], while broader AI-enabled DSS reviews highlight hybrid architectures that combine data-, knowledge-, and model-driven components [16]. In this context, we foreground a metrics-first evaluation approach and cross-reference these choices throughout the paper—most notably in Sections 2.8 and 3.1 [13], [17].

1.2 Novelty And Positioning

This work differs from prior AI-enabled DSS and helpdesk chatbots in three ways:

- *End-to-end NLP-to-analytics pipeline for knowledge institutionalization.* Beyond question-answering, the system captures conversational artefacts, stores structured cases, and surfaces analytics that support organizational learning and managerial decision-making positioned within classical DSS taxonomies (model-, data-, and knowledge-driven) and Intelligent DSS characteristics [9], [10].
- *SECI-grounded operational indicators for live deployment*. We link chat logs to organizational learning via First-Contact Resolution (FCR), Time-to-Resolution (TTR),

and recurrence rate, aligning with the SECI knowledge-creation perspective [11], [12] (see Methods).

- *Metrics-first evaluation protocol.* We pre-specify metrics and inclusion rules and report client-side time-to-first-suggestion, feedback-conditioned Helpfulness, and κ-based summary reliability, following guidance on transparent, human-centric chatbot evaluation [13].

Position within DSS taxonomies. In DSS terms, the design is hybrid—combining knowledge-driven components (captured cases and summaries), data-driven analytics (dashboards, KPIs), and algorithmic NLP capabilities—consistent with the IDSS view [9], [10].

2 MATERIAL AND METHOD

The proposed solution is a web-based application developed with ASP.NET Core MVC. The architecture follows the classic Model–View–Controller (MVC) pattern, separating back-end logic, presentation, and database access to maximize modularity and maintainability. Its primary goal is to assist IT-support personnel and end-users in diagnosing and resolving technical issues through AI-powered conversational guidance, while automatically recording each support session for later analysis.

2.1 Overall System Architecture

Figure 1 depicts the high-level data flow. Users interact with the Application Interface, which relays each request to a set of modular services. These modules, in turn, communicate with both a Microsoft SQL Server 2019 database and the OpenAI language-model API.

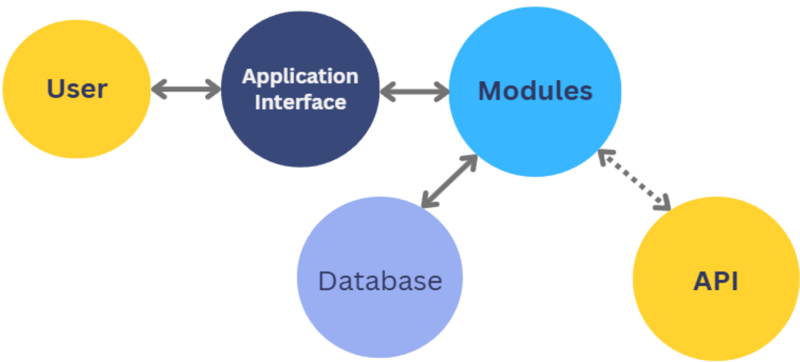

Figure 1. Overall system architecture illustrating data flow between the user interface, modular services, database, and API.

2.2 Chatbot Component

The chatbot integrates securely with the GPT-based OpenAI API. It receives natural-language queries, parses intent, and generates context-aware answers. All interaction is handled through asynchronous JavaScript (AJAX) calls, enabling real-time updates without page reloads.

The chatbot is responsible for accepting user questions, extracting meaning, and returning contextually appropriate responses. A feedback loop allows users to rate each answer, thereby supplying labelled data for iterative fine-tuning of system performance.

2.3 Interaction Sequence

Figure 2 shows the end-to-end sequence for a single helpdesk session:

1. User Message is submitted.
2. The API generates an answer.
3. The user receives the answer and provides feedback ("Helpful" or "Needs More Info").
4. When marked Helpful, the system (if configured) auto-generates a summary; when marked Needs More Info, the question is routed back to the chatbot for clarification.
5. All artefacts are saved to SQL Server for analysis.

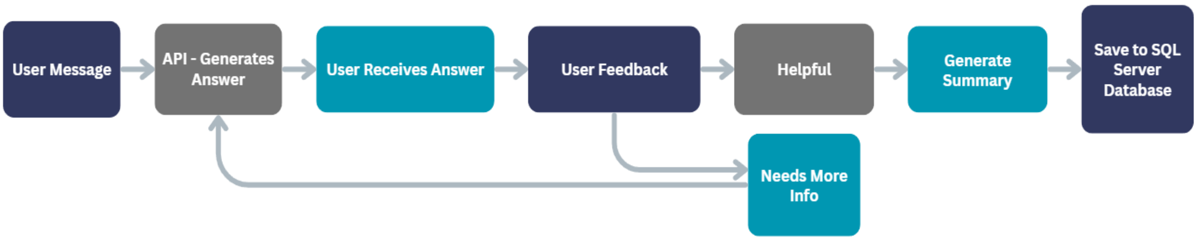

Figure 2. Chatbot interaction flow (scenario-based simulation). Branches reflect Helpful vs. Needs More Info outcomes; see Section 2.3.1 for the scenario set.

2.3.1 Scenario Set and Categories

We evaluated the system using a set of 50 representative IT-support scenarios derived from typical helpdesk tickets and FAQs. The aim was to mirror enterprise ticket mixes while covering common problem types and variations in wording. Each scenario specifies the user goal, initial message, and (where applicable) follow-up clarifications, enabling consistent exercise of the interaction flow in Figure 2 (see Table 1).

Sampling and rationale. We assembled 50 representative scenarios from typical helpdesk knowledge bases and standard operating procedures, aiming to (i) cover the top request types observed in enterprise IT support, (ii) include phrasing variations for the same intent (to stress the NLP layer), and (iii) balance short vs. multi-turn interactions to exercise both Helpful and Needs More Info branches in Figure 2. Category definitions and examples are summarized in Table 1; the observed distribution across our 50-scenario set is shown in Figure 4.

Table 1. Scenario categories and examples (taxonomy used in the 50-scenario set)

Category	Examples
Network Issues	DNS resolution, latency, routing
Software Installation	Installer errors, policy blocks
Email Access	IMAP/SMTP, mailbox quota
Hardware Malfunction	Disk/memory, device faults
Printer Issues	Queue stuck, driver/setup
VPN Login	Handshake/authentication
Other	Miscellaneous

Notes. (i) Scenario categories follow the taxonomy in Table 1; observed counts are visualized in Figure 4. (ii) Scenarios without user feedback are excluded from Helpfulness computations (see Section 2.8). (iii) The set supports both Helpful and Needs More Info branches in Figure 2.

2.4 Data Storage and Analytics

Every conversation, feedback entry, issue category, and AI-generated summary is logged in a dedicated SQL Server schema. These records are later queried to create statistical insights—such as frequently encountered issues, response effectiveness, and average resolution time—thus supporting organizational knowledge codification and reuse.

2.4.1 Data Handling and SQL Schema Design

- **Scope and logging.**

We log five artefact types for each session in a dedicated SQL Server schema: *conversations, messages, feedback, summaries,* and *categories*. For each conversation we store a stable session identifier, anonymized user role, and aligned timestamps captured both on the client (high-resolution, used for latency) and the server (receipt/persistence). Each user/assistant turn is stored as a *message* with its order index; *feedback* records whether the session was marked Helpful or Needs More Info; *summaries* hold the AI-generated synopsis and the rater label used in κ computation; *categories* map the session to the helpdesk taxonomy used in Table 1: Network Issues, Software Installation, Email Access, Hardware Malfunction, Printer Issues, VPN Login, Other.

- **Keys, integrity, and indexing.**

Primary keys are surrogate integers (IDENTITY). Foreign keys enforce relationships (*messages*, *feedback*, *summaries* → *conversations*; *conversations* → *categories*).

We enforce ***NOT NULL*** on critical fields (session id, timestamps, feedback flag, category id) and maintain audit columns (*created_at*, *updated_at*). Indexes target common analytical queries: clustered index on *conversations(session_id)*; non-clustered indexes on *(category_id, created_at)* and *(helpful_flag, created_at)*; composite index on *messages (conversation_id, turn_no)* for ordered retrieval.

- **Privacy and access control.**

No personally identifiable information (PII) is stored. User identifiers are omitted or pseudonymized at source; only role-level attributes (e.g., requester vs. admin) are retained for aggregates. Access follows least-privilege: the application service account writes; analytics consume read-only views.

- **ETL and analytical views.**

A nightly job materializes dashboard-ready aggregates: (i) **Time-to-First-Suggestion** (from client-side timestamps); (ii) **Helpfulness** conditioned on the presence of feedback; (iii) **recurrence rate** (fraction of incidents matching prior solved cases over a rolling window); and (iv) **Time-to-Resolution (TTR)** for first-contact resolution. The dashboard queries SQL **views**, not raw tables.

- **Data retention and backups.**

Raw logs are retained for N months per policy; summaries and aggregates persist longer, while detailed message payloads may be pruned. Backups: daily incremental + weekly full; point-in-time restore enabled.

- **Alignment with evaluation.**

This schema underpins our **metrics-first** protocol: client-side latency derives from front-end timestamps; **Helpfulness** uses only sessions with feedback; κ-based summary reliability uses stored rater labels. Scenario labels align with Section 2.3.1**.**

2.5 Front-end Implementation

The user interface is built with HTML, CSS, Bootstrap, and jQuery. Navigation relies on tab-based panels, keeping the client side lightweight and responsive. Administrators access a protected Analytics page where dynamic charts and summarized text outputs visualize chatbot performance and workload distribution.

2.6 Continuous Improvement Loop

Collected data are periodically re-analyzed to refine prompt templates and upgrade response quality. The explicit user-rating mechanism supplies ground-truth labels, enabling supervised enhancement of the underlying language model over time.

2.6.1 Theoretical Grounding: SECI

We ground organizational learning in the SECI model (Socialization–Externalization–Combination–Internalization), as described by Nonaka and Takeuchi [11] (see also Nonaka [12]). In our workflow, chatbot-guided dialogues help externalize tacit troubleshooting know-how into explicit case summaries; analytics and stored cases enable combination across incidents and team-wide internalization of effective practices. This operationalization is consistent with the SECI perspective and recent SECI-based applications [14].

2.6.2 Measurement Plan for Knowledge Institutionalization

During field deployment, we will track two longitudinal indicators to quantify knowledge institutionalization: (i) a reduction in the rate of recurring incidents, and (ii) a reduction in Time-to-Resolution (TTR) up to first-contact resolution (FCR). These indicators complement the continuous improvement loop in Section 2.6, where logged data inform prompt and template refinement as well as supervised updates to the model.

2.7 Evaluation Measures (Planned Live Deployment)

Beyond binary Helpful/Needs More Info, we will collect multi-dimensional UX indicators (perceived usefulness, trust, satisfaction, and intention to use) using 5–7 point Likert items. These will be mapped to TAM/UTAUT2 constructs and interpreted alongside operational KPIs during field deployment (e.g., FCR, TTR). Optionally, we will report scale reliability (e.g., Cronbach’s α) and analyze relationships between UX constructs and operational KPIs.

2.8 Metrics & Computation

We pre-specified the metrics and inclusion rules prior to running the 50-scenario simulation to avoid post-hoc bias (see Section 2.3.1 for scenario composition).

Helpfulness is computed as the number of sessions marked “Helpful” divided by the number of sessions that received user feedback. Sessions without user feedback are excluded from the denominator.

Time-to-First-Suggestion is measured from the client-side timestamp of the user’s submission to the moment the first suggestion is rendered in the UI; we report the mean ± standard deviation (SD) across sessions (timestamps are recorded at high resolution on the client). Where appropriate, we also report 95% confidence intervals alongside mean ± SD.

For summary-quality reliability, we report Cohen’s κ computed on binary agreement (acceptable vs. unacceptable summaries). The rater training, unit of analysis (summary–pair), and tie-breaking procedure are documented in Section 2.8.1.

Time-to-Resolution (TTR) is measured from the user’s initial submission (client-side timestamp) to the instant the session is marked resolved in the UI; we report mean ± SD where available (and 95% CIs where appropriate). In the scenario-based evaluation, TTR reflects scripted completion events rather than live ticket closure.

2.8.1 Inter-rater Reliability Procedure

Three raters used a shared codebook with positive/negative examples and completed a calibration round of 10 samples until consensus reached ≥90%. The unit of analysis is the (system summary, reference) pair. Raters assigned binary labels (acceptable vs. unacceptable) independently and in random order; they were blinded to each other’s decisions. Cohen’s κ was computed on the binary labels to quantify agreement. In case of ties or unresolved disagreements, a senior rater adjudicated after a brief discussion; all disagreements and adjudication notes were logged. Where appropriate, κ is reported together with 95% confidence intervals.

3 RESULTS AND DISCUSSION

The developed AI-based decision support system was tested within a controlled environment by simulating user interactions with IT-related problem scenarios. During the initial testing phase, 50 representative sessions were conducted using typical helpdesk queries such as password reset, printer connectivity, and VPN configuration. The system successfully guided users through each problem-resolution path and stored the corresponding solution data in the back-end database.

3.1 Chatbot Performance

The chatbot was evaluated using four indicators aligned with Section 2.8: Helpfulness (feedback-conditioned), Time-to-First-Suggestion (client-side), summary-quality reliability (Cohen's κ), and feedback completion rate.

Across N = 50 scenario-based sessions:

- Helpfulness: 88% of evaluated sessions were marked "Helpful" (denominator includes only sessions with user feedback; see Section 2.8).
- Time-to-First-Suggestion: 1.68 ± 0.21 s (mean ± SD, client-side), measured from submission to the first suggestion rendered in the UI (client timestamps recorded at high resolution; see Section 2.8).
- Feedback completion rate: 76% of sessions received user feedback.
- Summary reliability: Cohen's κ = 0.87 on binary agreement (acceptable vs. unacceptable), computed per the inter-rater procedure in Section 2.8.1 (unit of analysis: summary–pair; adjudication in case of ties).

These results indicate that the system produces timely and generally helpful suggestions under controlled conditions, while generating summaries that are linguistically consistent and understandable. Because the evaluation is scenario-based rather than live, external validity should be interpreted with caution; see Section 5 (Limitations). Calculation details for all metrics are provided in Section 2.8.

AI-Generated Summary

"The user reported issues with printer connectivity.

The problem was resolved by restarting the spooler service.

Recommend internal procedure #104 for recurrence."

Figure 3. Example AI-generated summary from a simulated helpdesk session. The summary is logged to support knowledge capture and subsequent analytics (see Section 2.4).

3.2 Decision Support Insights

The administrator dashboard aggregates logged data into visual analytics. Figure 4 shows the observed distribution across our 50-scenario set: Network Issues constituted the largest category (28%), followed by Software Installation (20%) and Email Access (16%); values above bars indicate counts (N = 50).

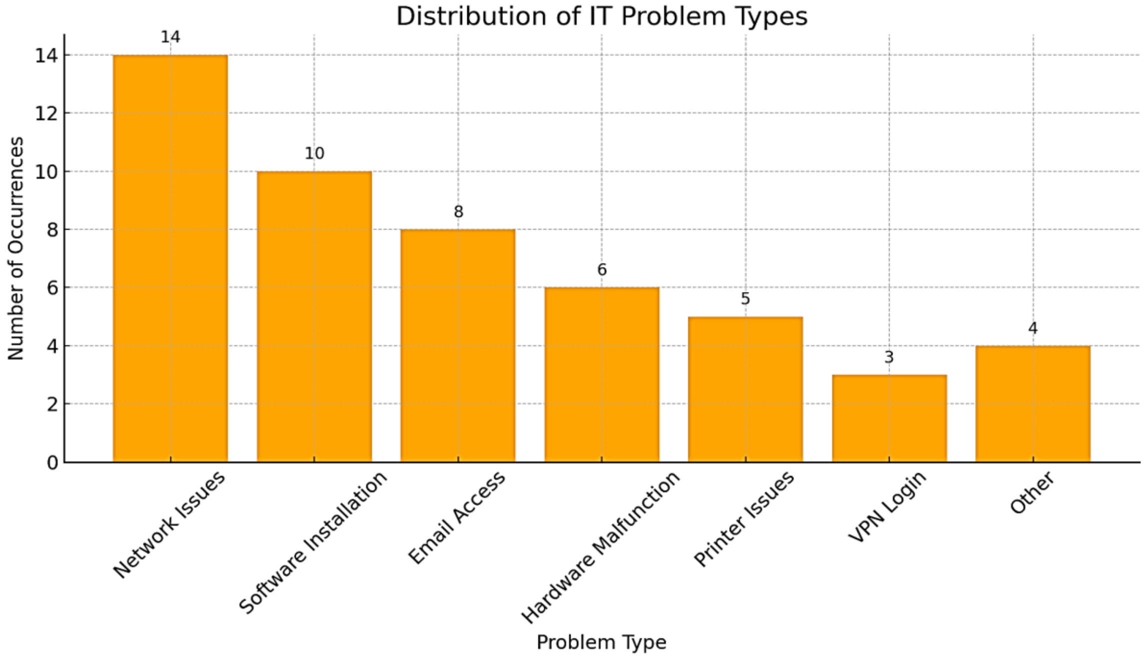

Figure 4. Distribution of IT problem types across 50 simulated sessions. Values above bars indicate counts.

Time-to-Resolution (TTR) averaged 3.2 minutes across the 50 scenarios (see Section 2.8). In this scenario-based evaluation, "resolution" refers to the scripted completion of the task in the UI rather than live ticket closure.

These findings align with prior reports that AI support can reduce human workload, accelerate solution delivery, and enable real-time knowledge capture—while emphasizing transparency and trust in organizational adoption [5], [6], [7].

In our evaluation, the high Helpfulness, sub-two-second Time-to-First-Suggestion, and structured knowledge capture align with the transparency/trust and organizational-learning principles emphasized by Chowdhury et al. and Romero-Gómez et al. [1], [7].

3.3 Responsible AI & Explainability

Given the use of a black-box foundation model, we balance risks through decision-trace logging, concise rationales, access control, and data minimization. As future work, we will conduct comparisons against an open-source base model and perform ablation studies on retrieval components to assess traceability and robustness.

4 CONCLUSION AND SUGGESTIONS

This study aimed to design and implement an AI-powered decision-support system tailored for IT support units. The proposed system combines a natural-language-processing-based chatbot interface with a structured feedback-and-analytics layer to enhance problem-resolution efficiency and provide data-driven managerial insights. Given that our assessment is simulation-based, external validity should be treated with caution; see Section 5 (Limitations).

The project demonstrates that AI-powered interactions can effectively assist users in resolving common technical issues and can codify tacit troubleshooting knowledge, thereby fostering organizational learning. The chatbot's capability for contextual adaptation and real-time interaction makes it particularly valuable for IT departments aiming to standardize troubleshooting procedures, reduce workload, and improve response times [3].

As no live deployment has been conducted yet, real-world performance and behavioral responses may differ; future field studies will validate the metrics and UX constructs in production settings.

For future work, the system could be extended with multi-language support, adaptive learning based on user feedback, and deeper integration with organizational ticketing systems. Additionally, responsible-AI requirements—such as transparency, data privacy, bias mitigation, explicit user consent, robust cybersecurity measures, adherence to ethical guidelines, and policies fostering responsible AI deployment—must be addressed in real-world implementations to ensure ethical and effective use [6], [7].

5 LIMITATIONS

This study was evaluated using 50 researcher-crafted scenarios rather than live enterprise data. As a result, natural-language variability, user impatience, and heterogeneity in technical proficiency may not be fully represented, and operational conditions (e.g., network load, ticketing integrations) were not exercised. Findings should therefore be interpreted with caution until field deployment is completed (see Section 6, Future Work). The need for field validation aligns with prior DSS evaluations conducted in real-world settings [15].

6 FUTURE WORK

We plan to integrate the system with enterprise ticketing platforms (e.g., Jira/ServiceNow) and evaluate it via live A/B testing. Key KPIs to be tracked include First-Contact Resolution (FCR), Time-to-Resolution (TTR), and the rate of recurring incidents, enabling comparative analyses against the current baseline.

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Conflict of Interest Statement

There is no conflict of interest between the authors and any third party regarding the content, data, or results presented in this study.

Statement of Research and Publication Ethics

This study complies with all research and publication ethics. No real user data was collected or processed during the implementation and testing phases. All findings were derived from simulated test scenarios designed solely for academic purposes.

Artificial Intelligence (AI) Contribution Statement

AI tools were used in this study. Specifically, we used OpenAI's language-model API (GPT-4 class; gpt-4o-mini) during system prototyping to design prompts and generate chatbot responses within the software being evaluated. In preparing the manuscript, ChatGPT was used only for limited English grammar and phrasing edits. All conceptualization, study design, simulation setup, quantitative analysis, tables, and figures were performed by the authors. All AI outputs were reviewed and verified by the authors, who take full responsibility for the content.

Contributions of the Authors

Şahin ZAMBAK: Conceptualization; Methodology; System design; Software development; Implementation; Validation; Formal analysis; Investigation; Data curation; Visualization; Writing – original draft; Writing – review & editing.

Tahsin ÇETİNYOKUŞ: Supervision; Project administration; Resources; Administrative support; Writing – review & editing.

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