AI-Driven Autonomous Knowledge Assistants for Enterprise IT Helpdesks

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ABSTRACT: In today's complex information technology (IT) environment, enterprises utilise increasingly sophisticated products and know-how to support critical business operations. Conventional IT assistance mechanisms are costly in terms of time, human resources, and finances. An alternative strategy is to implement an enterprise IT helpdesk knowledge assistant to answer questions and solve problems, primarily for first- and second-line IT Support and Service Desks. Such an autonomous knowledge assistant is an augmented and continuously assisted chatbot powered by artificial intelligence (AI) technologies. It supports omnichannel access, replicates the judgement and experience of human experts, continuously gathers insights from support conversations, provides recommendations for good practices and detection-prevention-action workflows, and ensures data governance. Although the enterprise knowledge assistant is primarily geared towards IT, it can be adapted for self-service in different business functions and industries.

AI-driven autonomous knowledge assistants deploy AI technologies, including advanced Natural Language Processing (NLP) techniques, to ingest content, train large Transformer text generators with dedicated knowledge, and converse with users, drawing on internal company resources such as documentation, previously closed incidents, troubleshooting guides, run-book procedures, best practices, and ServiceNow CMDB data. Users may be service desk agents, system administrators, remote work users, colleagues providing assistance, or anyone else engaged in the operations and maintenance of the IT enterprise systems. These autonomous knowledge assistants overcome the data-privacy challenges of ChatGPT and similar systems by ingesting external content to create their own proprietary large language model.

KEYWORDS: Enterprise IT helpdesk; autonomous self-service assistant; autonomous knowledge assistant; knowledge management; data governance; artificial intelligence; data privacy; AI bias; knowledge graph; operational automation; intelligent IT assistant; virtual assistant; user experience; autonomous troubleshooting; active knowledge base.

I. INTRODUCTION

The amount of information being generated and shared across enterprises is rapidly accelerating, especially in the technology domain, by leveraging online platforms like Confluence, SharePoint, or even OpenAI systems. Even in enterprise IT helpdesks, where information used to be extremely structured, the proliferation of new programming languages, environments, platforms, and technologies continues to significantly augment the size and complexity of the available knowledge. As a way to optimize for this explosion of information, enterprises must invest in IT self-healing and self-service strategies.

One of the core aspects of self-service and self-healing systems is the establishment of an AI-driven autonomous knowledge assistant. Currently, many Knowledge Management systems are heavily dependent on manual processes for content creation and approvals, error-free data entry in a structured format, and frequent content updates by human curators. Manual processes eventually result in content being stale, outdated, or incorrect. This paper proposes a Knowledge Assistant that uses a data-source-agnostic approach for data ingestion and wrangling to onboard data from any existing online knowledge shareable platform, followed by an AI-driven representation and reasoning mechanism over the ingested data, enabling advanced self-service troubleshooting, proactive issue detection and prevention, learning from user inputs, and other capabilities.

A core enabler of truly self-service and self-healing systems is the deployment of an AI-driven autonomous Knowledge Assistant that minimizes reliance on manual knowledge management processes. Traditional Knowledge Management

(KM) platforms depend heavily on human-driven content creation, structured data entry, review cycles, and periodic updates, which often result in stale, inconsistent, or outdated information. In contrast, the proposed Knowledge Assistant adopts a data-source-agnostic ingestion and wrangling framework capable of onboarding content from diverse online knowledge repositories, collaboration platforms, documentation systems, and operational logs without requiring rigid formatting standards. Once ingested, the system leverages AI-driven representation learning and reasoning techniques—such as semantic embeddings, knowledge graphs, and contextual inference—to transform unstructured and semi-structured data into an intelligent, queryable knowledge fabric. This enables advanced capabilities including automated root-cause analysis, contextual troubleshooting guidance, proactive issue detection and prevention through pattern recognition, and continuous learning from user interactions and feedback. By shifting from static documentation to dynamic, self-evolving knowledge intelligence, the Knowledge Assistant becomes a foundational pillar for scalable, resilient, and adaptive digital operations.

Fig 1: AI powered Help Desk improves customer service

1.1. Background and Significance

In an enterprise information technology (IT) context, knowledge workers often require assistance to resolve problems with enterprise applications such as Jira, Confluence, and Office 365. These companies often use internal IT helpdesks to address these problems. Most helpdesk tickets, however, are knowledge-intensive and repetitive and could therefore be easily resolved by a self-service system. Enterprise IT tickets often also contain information related to the failure of IT services provided to the business. Many of these failures can be prevented or their impact minimized if detected in advance. Enterprises can therefore equip their IT helpdesks with a self-service system that correctly and reliably resolves tickets filed by knowledge workers, along with a proactive issue detection and prevention capability. Such a system can be classified as an AI-driven autonomous knowledge assistant and can provide enormous cost benefits to the business.

The AI-driven autonomous knowledge assistant for IT helpdesks provides three autonomous capabilities: self-service troubleshooting for frequently asked questions or common issues, proactive detection of impending problems that affect business-critical services, and an accelerated incident response and resolution capability. The first two capabilities can minimize operating costs by reducing the need to engage support staff, while the third enables the business to respond more quickly to IT incidents. Knowledge-intensive tickets, which require a significant amount of support effort, can be classified by a semi-automated categorization and routing subsystem and then resolved either automatically or by human experts. Successful self-service troubleshooting and proactive detection of business-impacting incidents can also improve the quality of service and business satisfaction.

Equation 1: Ticket deflection rate

Let:

- N = total tickets in a period (e.g., per month)
- N_d = tickets resolved by the assistant end-to-end (deflected)

Definition

$$D = \frac{N_d}{N}$$

Step-by-step

1. Start with "fraction of tickets deflected" = (deflected tickets) ÷ (total tickets)
2. Substitute symbols: $D = N_d/N$

II. BACKGROUND AND RATIONALE

Diminished human resources and disrupted employment have increased the difficulty of providing ever more efficient IT support in a climate of rising user expectations. Outsourcing the service desk to offshore suppliers has helped keep costs down but caused issues in terms of resolution time, multilingualism and cultural affinity. User self-service could also reduce costs, but providing effective help through browsing is a significant knowledge management challenge. Ultimately, the ideal solution would be to redirect the daily flow of a service desk specialist's work into sole or partial self-service tools.

Autonomous Knowledge Assistants (AKAs) can interrogate supplier knowledge bases, service desk tickets, user manuals, and proprietary and open-source technical documentation to answer Level 1 service desk queries at any time from anywhere. They can learn from being read—natural language and knowledge representation may improve by being consumed by humans—and help detect issues before they affect multiple users. In addition, they can execute simple tasks and update their underlying knowledge pools so that users can easily self-serve routine IT requests such as password resets.
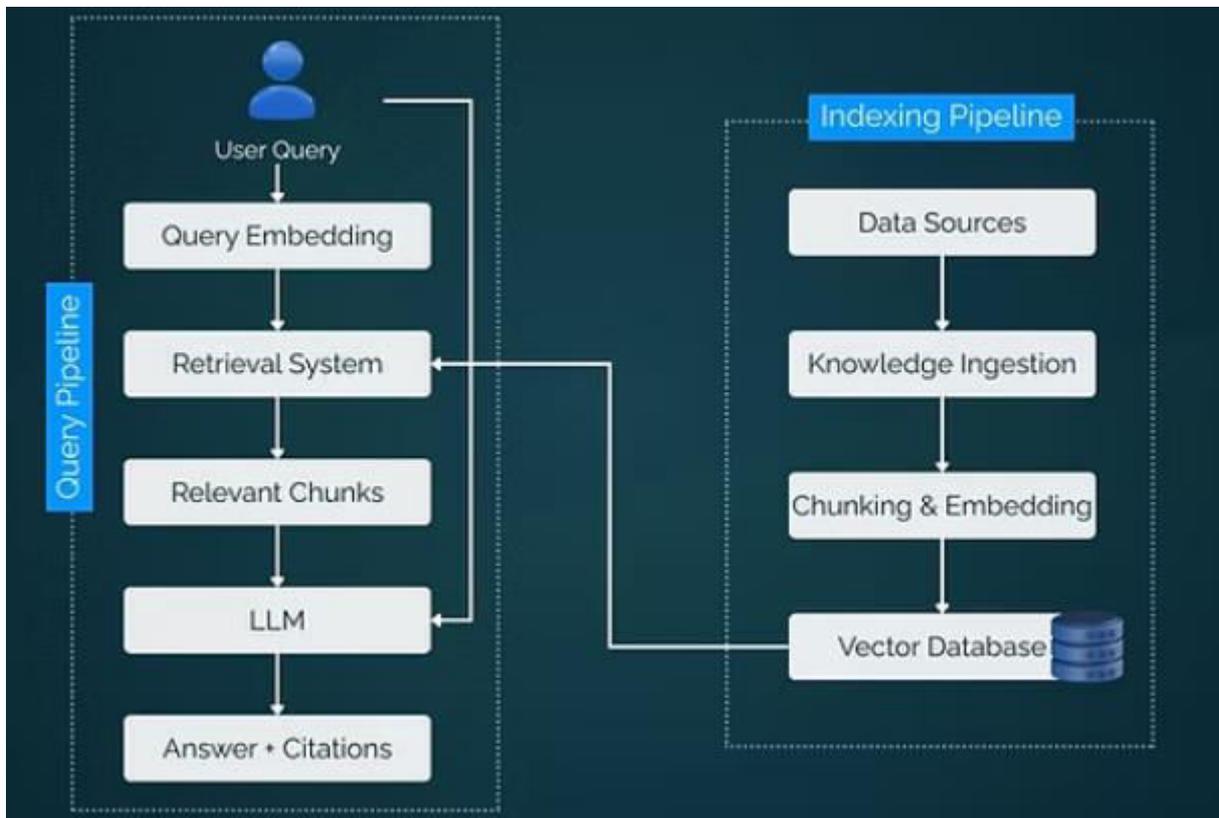

Fig 2: Background and Rationale of AI-Driven Autonomous Knowledge Assistants

2.1. Research design

The design of this research is a synthesis of existing approaches for creating intelligent voice-enabled self-service autonomous knowledge assistants that can reside in enterprise help-desk systems and deal with Level 1 requests. The autonomous assistants are designed to be knowledgeable enough to resolve a large number of help-desk requests completely end-to-end without human intervention. Specifically, the focus is on help-desk technology built around chatbots and Virtual Agents as the User Interface and Knowledge Management Systems or ITIL-based Knowledge Management Systems as the Knowledge Base.

However, most existing self-service autonomous knowledge assistants designed for Level 1 requests must still transfer a large number of requests to human agents. Furthermore, they also suffer from issues related to data privacy, bias in AI, user experience, and explainability and transparency. These issues are taken into account by adding appropriate components to the synthesis and by building an analytical framework for such autonomous and self-service assistants in enterprise help-desk service systems.

Equation 2: Baseline cost vs post-assistant cost
Let:
- C = average cost per ticket (labor + overhead) in the period
- C_{fixed} = fixed monthly cost to run the assistant (infra, monitoring, governance, etc.)
- N = total tickets
- D = deflection rate

Baseline monthly cost (no assistant)

$$\text{Cost}_0 = N \cdot C$$

Derivation
- Each ticket costs C
- There are N tickets
- Total $= N \times C$

III. ARCHITECTURAL FRAMEWORK

Figure 1 depicts the architectural framework underlying the implementation of an autonomous KA focused primarily on enterprise IT helpdesks. The review of the existing research, along with industry best practices, highlights the crucial components of data ingestion and wrangling, knowledge representation and reasoning, and risk mitigation strategies associated with data privacy, confidentiality, and quality. The specialised architecture brings together state-of-the-art natural language processing, image processing, deep neural networks, knowledge-based systems, and data engineering, which facilitate the development of self-service solutions.

Modern enterprise IT ecosystems support a wide range of products and services with complex integration. Hence, the autonomous KA should provide near-to 100% coverage of use cases that are being dealt with by the IT helpdesk. A detailed analysis of earlier support tickets should yield a comprehensive union of primary and secondary user intents. Primary intents group queries that have similar operational features and usually require similar resolution steps, while secondary intents relate to documented resolutions that have not yet been tried by the end users. With such a representation, self-service troubleshooting and guidance solutions can be built. Furthermore, machine learning-based visual assistance, incorporating findings from domains such as cloud-native application security, can be employed for the remaining use cases where support is absent or minimal.
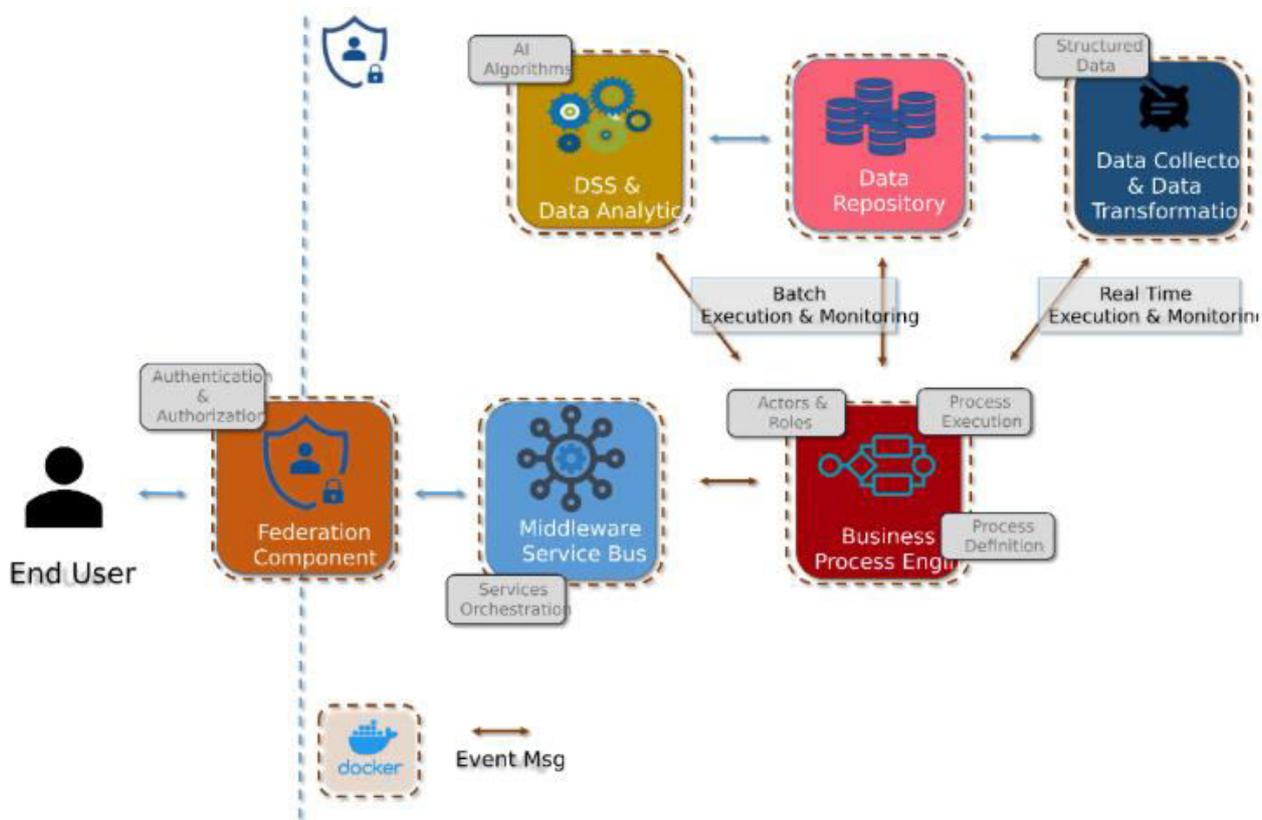
Fig 3: A Knowledge-Driven Framework for AI-Augmented

3.1. Data Ingestion and Wrangling

Enterprises generate vast amounts of structured and unstructured data on a regular basis. Data ingestion is an end-to-end process that involves the identification and acquisition of relevant data sources, ingestion of diverse data types, and the structuring or cleansing of messy data. For self-service KBs, data ingestion and wrangling is a critical first step, as the efficacy of subsequent KRR and KRR processes relies on its quality.

The proliferation of multiple communication channels within organizations generates vast amounts of unstructured data, with prominent examples such as email, chat applications, knowledge-sharing platforms, incident management systems, and even social media platforms. Personal communication channels can also serve as indirect sources of SLO-related data, especially for issues that relate to specific business lines or technology stacks. For helpdesk organizations, these sources contain insights into two critical categories of knowledge: problem resolutions and service level objective (SLO) violations. A large percentage of incidents typically involve service outages or performance degradations, along with the corresponding workarounds or resolutions. Additionally, these incidents define the SLOs committed to by the helpdesk organization. SLOs represent an enterprise's commitment to delivery timelines, quality, and performance, and SLO violations can lead to financial or reputational losses.

3.2. Knowledge Representation and Reasoning

The knowledge representation and reasoning (KRR) component of the proposed framework employs a unified, task-independent ontology to address two key tasks. First, it serves the traditional knowledge base (KB) role of representing the helpdesk knowledge-base contents and related source documents in a machine-readable format. This enables provisioning of data to agent-based or passive filtering architectures for self-service troubleshooting and other applications. Second, it imbues the knowledge base with reasoning capability, enabling the KRA to be treated as the `external reasoning engine' in the overall architecture.

The KRR component uses the ontology for domain KRR and construction of the `Inferred Knowledge Base' (IKB). The IKB is an updated version of the KB, containing additional information inferred from the KB and IKB content and the ontology, using first-order predicate logic. The reasoning capability of the KRA is demonstrated with two use-cases: a sample `context-setting' incident ticket and the `pro-active monitoring, detection and prevention' use-case requiring

inference. The example context captures the user's perspective, detailing the user's home system set-up, home internet connection, and various applications that may be affected; knowledge captured as part of the context-setting process is a necessary enabler for the automatic detection and notification of system issues that could directly impact the user's productivity.

Equation 3: Net savings
Monthly savings

$$S_{\text{month}} = \text{Cost}_0 - \text{Cost}_1$$

Substitute:

$$S_{\text{month}} = NC - (N(1-D)C + C_{\text{fixed}})$$

Distribute:

$$S_{\text{month}} = NC - N(1-D)C - C_{\text{fixed}}$$

Factor NC:

$$S_{\text{month}} = NC(1 - (1-D)) - C_{\text{fixed}}$$

Since $1 - (1-D) = D$:

$$\boxed{S_{\text{month}} = NCD - C_{\text{fixed}}}$$

Annual savings

$$S_{\text{year}} = 12 \cdot S_{\text{month}}$$

IV. CAPABILITIES AND USE CASES

By eliminating repetitive, low-value query transactions, an AI-driven autonomous knowledge assistant enables helpdesk staff to focus on complex queries requiring human judgment and reasoning, thereby augmenting and enhancing their capabilities. However, the utility of such an assistant is not only limited to self-service. Being plugged into a broad ecosystem of enterprise IT systems (e.g., logs from outages, incidents, changes, and problems; topology information; past queries; and knowledge bases), these autonomous agents can proactively digest information and generate useful insights for current and upcoming issues.

Four primary use cases are envisaged: self-service troubleshooting, proactive detection of potential issues causing downtime, prevention of actively occurring issues from escalating into critical outages, and demand/request forecasting to enable better resource planning in helpdesks and more broadly in enterprise IT. Each use case is briefly elaborated below.

Additionally, non-IT staff can engage with Autonomous Knowledge Assistants in natural language instead of technical language. Freedom of formulation without grammar stress can aid expression clarity and completeness, leading to better responses.

Fig 4: AI Helpdesk Benefits, Use Cases

4.1. Self-Service Troubleshooting

A salient feature of Autonomous Knowledge Assistants in enterprise IT helpdesks, is self-service troubleshooting. They can access historical incident reports, comprehend symptoms and resolutions, and utilize parsing and reasoning skills over the entire knowledge base to facilitate users in resolving issues without needing to reach out to the helpdesk. Such capabilities can thereby free Helpdesk personnel to concentrate on more complex and less-automated issues.

For instance, if an enterprise application stops responding for certain users without any associated incidents, those users can search for help in the knowledge base. The users can simply describe the issue, which expresses symptom(s) of an unresolved incident. The Autonomous Knowledge Assistant can then perform a symptom-to-solution mapping to identify past incidents with a matching symptom and present their resolutions. A more advanced Autonomous Knowledge Assistant can also reason through the knowledge base to eliminate misleading resolutions. For example, the console of a web application throwing server errors can indeed be a symptom of multiple different incidents with different resolutions, some of which may be applicable to the current situation while others not. An Autonomous Knowledge Assistant incorporating this level of reasoning can not only suggest past similar incidents but can also accurately score the applicability of their resolutions.

Equation 4: Operational performance metrics equations (how "correct" the assistant is)

Let:

- TP = true positives (assistant solved correctly)
- FP = false positives (assistant claimed solved but wrong)
- FN = false negatives (assistant failed when it could have solved)

$$\text{Precision} = \frac{TP}{TP + FP}$$

Derivation

- "Of everything the assistant said it solved, how many were correct?"
- Correct solved = TP
- Total claimed solved = TP + FP
- Ratio = TP/(TP+FP)

4.2. Proactive Issue Detection and Prevention

Two distinct features of the Self-Service Troubleshooting capability of autonomous Knowledge Assistants be discussed and illustrated separately in the following two sections. The current section describes the proactive detection of issues before they impact the employees. This capability extends the self-service troubleshooting function and shifts the focus

from post-factum reactive troubleshooting to proactive detection of potential problems. Assistance is provided to IT departments in detecting emerging problems and, when appropriate, proactively warning users about issues that are likely to occur in the near future, along with suggested workarounds.

Detecting emerging issues requires a significant amount of operational incident and problem data to analyze. Here the Knowledge Assistant identifies patterns in incidents and problem tickets through association rule mining and anomaly detection techniques. Anomaly detection models can be trained using classic techniques such as k-means clustering, time-series analysis, and regression analysis, or with advanced deep learning-based techniques. Continuing with the example of the network drive browsing issue, the Knowledge Assistant has begun to identify incidents indicating slow browsing of shared network drives, due to suspected storage array performance issues. So far these incidents have only occurred for a single user, but several incidents of file access response latency in the same storage area have been noted that do not appear to be related to the user's Internet connection. The Knowledge Assistant detects these patterns and alerts the IT department that further monitoring of access-related incidents to this storage area should be undertaken, and that users might be warned about potential problems when the patterns become more significant.

V. DATA GOVERNANCE AND SAFETY CONSIDERATIONS

While AI and ML capabilities have greatly expanded, building enterprise applications that guarantee safety and compliance with governing regulations is still a significant challenge. Data governance issues such as user privacy, bias, and a lack of transparency and explainability need to be prioritized during the development process. The architectural framework described in this paper tackles these issues while creating an AI-driven autonomous knowledge assistant.

Data privacy and confidentiality are of utmost importance when training AI or ML systems, especially when sensitive personal information is involved. Therefore, organizations need to take different measures to prevent such data from leaking into training datasets. Information leakage related to sensitive data, such as personally identifiable information, company secrets, passwords, and confidential business communication, must be thoroughly examined and eliminated from the training datasets. Addressing these privacy and confidentiality concerns is critical for large organizations like banks, defense contractors, and healthcare companies, where even a single case of compromised sensitive data can have extremely grave consequences. One approach is utilizing differential privacy, which accounts for the relevant privacy laws and issues while developing a model. The model provides misleading or distorted output, which does not affect the overall utility but guarantees that no extra information about individuals present in the data can be revealed.

Protecting data privacy and confidentiality is a fundamental requirement when developing and training AI and machine learning systems, particularly in environments that handle sensitive information. Organizations must implement rigorous data governance practices to ensure that personally identifiable information (PII), financial records, trade secrets, passwords, and confidential communications are not inadvertently incorporated into training datasets. This involves conducting thorough data audits, applying anonymization and encryption techniques, restricting access controls, and continuously monitoring for potential data leakage. For highly regulated sectors such as banking, defense, and healthcare, the consequences of exposing sensitive data can be severe—ranging from legal penalties and financial losses to reputational damage and national security risks. One effective strategy to mitigate such risks is the use of differential privacy, a technique that introduces carefully calibrated noise into the training process. By slightly distorting outputs in a mathematically controlled way, differential privacy preserves the overall utility and accuracy of the model while ensuring that no specific individual's information can be identified or inferred. This approach helps organizations comply with privacy regulations and strengthens trust in AI systems by embedding privacy protections directly into the model development lifecycle.

Baseline vs post-AKA variable cost (illustrative)
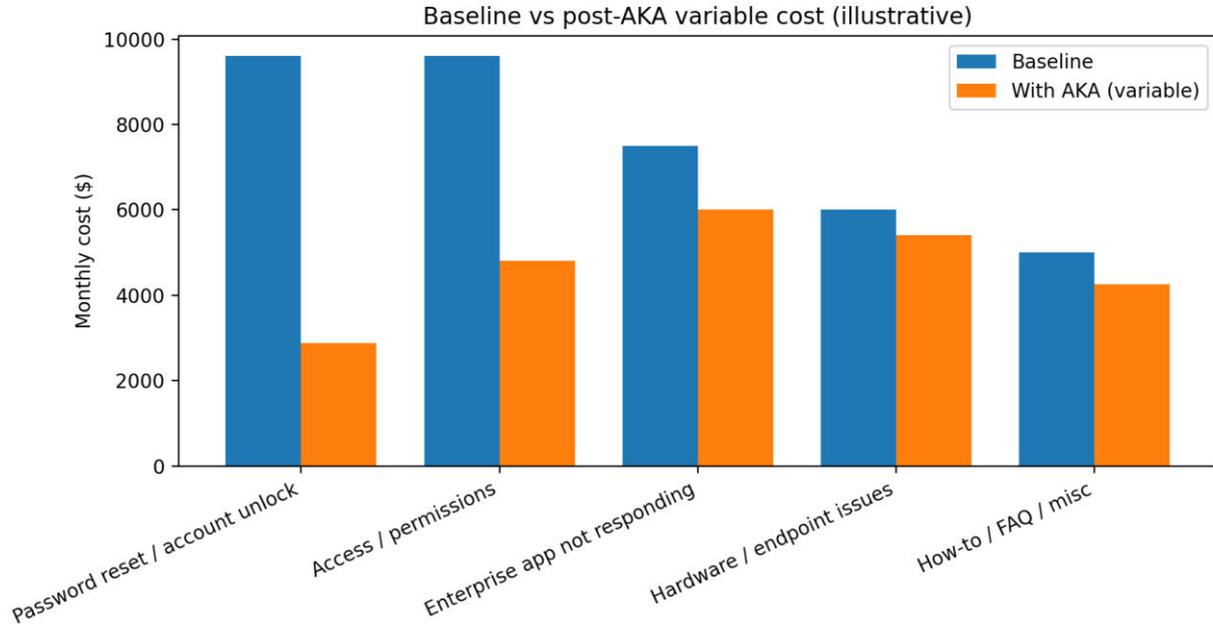
5.1. Data Privacy and Confidentiality

Privacy has emerged as a core business concern. For Internal Information Sources, Privacy can be protected in several ways. Customer Support requests, responses and Knowledge bases recorded by the Organisation are sources available for Data Ingestion. Internal Security Policies can provide further Data Configuration rules to avoid the automatic ingestion of privacy-sensitive information. Security Architecture should ideally stop such sensitive content from ever appearing in the first place. However, organisation-enterprise Knowledge finding does remain challenging, requiring the broadest coverage possible. The Organisational enterprise could therefore start by allowing new Knowledge to be ingested regardless of sensitive content. Data Wrangling rules can be configured to tag sensitive content, and setting up an information style guide will identify the people who remove such tagged content from ingestion trails of internal knowledge bases. Enabling enterprise Knowledge Share will then provide broader coverage of samples to improve the Data Ingestion process and Internal Knowledge Creation for the Customer Support System.

Use Cases designed for Association engine, that recommend Knowledge from Customers ? Services ? Taking the same action and tagged as Private Customer Feedback with Restricted access can help easy detection of Knowledge containing privacy or Enterprise Security breach threats.In such cases, automation without human validation of Knowledge sampled from customer support interactions should be disabled. Hence evaluation of EUC Knowledge Share, association act and Data Configuration rules will provide adequate privacy support.

Equation 5: Adoption / user-experience metrics equations (breadth, depth, sentiment)

Let:

- U_a= active users in a period
- U_e= eligible users (target population)

$$\text{Breadth} = \frac{U_a}{U_e}$$

Let:

- S= number of sessions (or queries) in the period

$$\text{Depth} = \frac{S}{U_a}$$

Let:

- p= number of positive ratings
- n= number of negative ratings

- $t = p + n$

A simple normalized score:

$$\text{Sentiment} = \frac{p - n}{t}$$

5.2. Bias, Transparency, and Explainability

Ensuring the elimination of bias in the KAs poses a formidable task for data scientists who are monitoring the data pipeline. Bias in AI systems can originate from multiple sources including historical and training data, development algorithmic bias as well as users' expectations and perceptions of the AI systems. These biases lead to unfair, erroneous or harmful outcomes in any type of Knowledge Assistant when interaction with non-dominant groups is likely. KAs should be developed and trained with ways to fairly treat all users and the ability to detect and correct bias whenever it may occur. Monitoring mechanisms should focus on reporting and intervening in algorithmic bias, in fairness of treatment across demographic-inflected sub-communities present within training datasets, and in satisfying ethical expectations. In addition, the KAs' decision-making processes should be sufficiently transparent, interpretable and explainable to the users.

Support for the user's understanding and interpretation of AI decisions may also address the widely-held danger that users come to rely on AI systems too much such that their own expertise wanes. To the extent that KAs display interpretable and easily understood decision-making processes, users can retain and deepen their autonomous knowledge and expertise while learning how and when it is necessary and useful to follow KA recommendations. Users' polished knowledge about the ka decision-making could also allow them to be trustworthy advisers to co-workers seeking second opinions and justification of the KA response.

VI. EVALUATION METRICS AND VALIDATION

The operational performance of an AI-powered, autonomous knowledge assistant may be evaluated using business metrics related to either cost reduction or performance improvement. Cost-saving area metrics indicate the potential annual savings arising from the assistant's ability to deflect a percentage of helpdesk tickets. These might include IT support ticket expenditure and resolution cost metrics, such as savings from annual staff cost based on the estimated number of tickets addressed by the assistant. Such metrics will assess whether or not the assistant delivers an overall quantifiable benefit to the services business unit that manages IT Helpdesk operations.

Crucial in determining the assistant's viability is the business's desired user uptake across these features. Given these self-service capabilities, which unlike conventional FAQ pages or knowledge containers, are much more interactive and human-like, user uptake is a pre-requisite signal for any time-served autonomous virtual assistant within an organization's IT Helpdesk. Importantly, uptake is not sufficient by itself, as users need to perceive value in the assistant's usage and consequently take pleasure in interacting with it. Three primary user experience and adoption metrics will therefore be monitored: usage distribution breadth and depth; feedback sentiment; and usage experience enjoyment.

Example monthly ticket volume by type
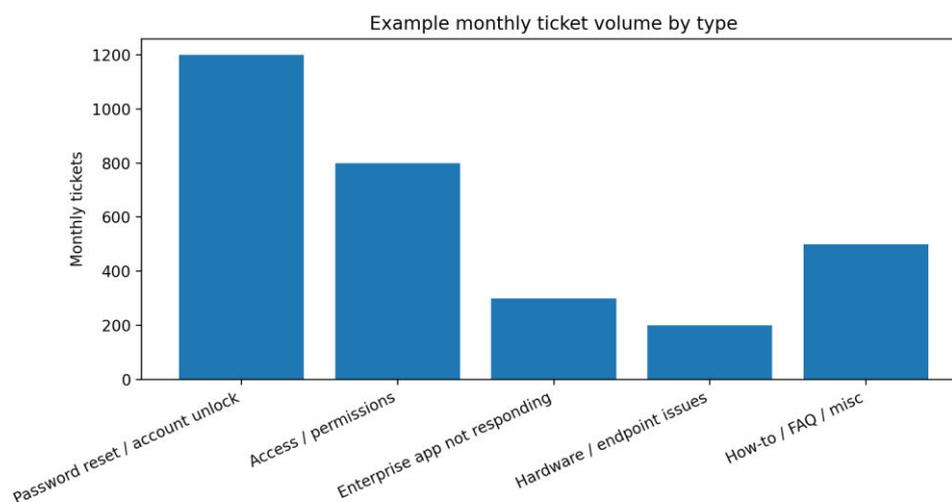
6.1. Operational Performance Metrics

Operational performance metrics focus on assessing the core problem-solving capabilities of an autonomous knowledge assistant during interactions with users. This can be accomplished by evaluating the outcomes of the assistant's troubleshooting or support request resolution processes using well-designed output assessment criteria.

Traditionally, output assessment has been executed manually by human evaluators, which can be a tedious, expensive, and even unreliable or inconsistent process. For this reason, operational performance metrics are frequently viewed more as a research endeavour rather than a maturity step in the deployment of such systems. However, with the availability of large sets of historical support interactions (such as incident tickets or support chat logs), automatic output assessment represents a much more accessible avenue for operational evaluation. Whenever a past interaction was handled by a human agent, the ground truth and output assessment criteria are necessarily available. Such a comparison is also particularly valuable, as human agents still represent the golden standard in support request resolution. More generally, with the large amount of logically documented knowledge in the knowledge base, any interaction can be reconstructed as a troubleshooting flow. The outcome of this trouble flow can also be compared to the outcome of the past interaction to verify both its correctness and effectiveness. For conversational systems, past interactions provide additional ground truth for the assessment of conversational coherence.

6.2. User Experience and Adoption Metrics

Beyond technical metrics, assessing user experience and adoption rates is crucial for validating the effectiveness of autonomous knowledge assistants in IT helpdesks. Positive user experience leads to higher usage levels, augmenting operational performance and lowering business costs. Empirical exploration, survey research, and user trials on actual helpdesk systems validate the framework's potential impact on user experience.

User experience can be gauged using established models like the Technology Acceptance Model (TAM) or the Unified Theory of Acceptance and Use of Technology (UTAUT). Evaluation of user experience and changes in usage volume and propensity is vital for successful implementation and adoption.

Consumer-oriented digital media or e-commerce systems have demonstrated the relationship between a positive customer experience and repeat usage. User experience can be assessed through existing models such as the Technology Acceptance Model (TAM) or the Unified Theory of Acceptance and Use of Technology (UTAUT). Validation of the perceived user experience and experience-driven changes in the volume and propensity to use enterprise support systems is vital to driving the successful implementation of an AI-driven solution.

VII. CONCLUSION

Enterprise IT Helpdesks have always needed to know what trouble is on the horizon, and provide answers for issues before they arise. Most would agree that presently, they are not achieving that goal. IT Helpdesks' key success factors are their response time – the first measure of end-user experience – and the accuracy of their answers. AI-Driven Autonomous Knowledge Assistants change this paradigm – providing a self-service troubleshooting tool for end-users that is so accurate it meets or exceeds the level of a human expert.

However, these Autonomous Knowledge Assistants offer far more than just a self-service tool. They understand the conversation – allowing the exchange of diagnosis questions and answers to happen naturally. They learn from the conversation itself and can propose a monitoring rule that can be automatically ingested in a suitable monitoring system. Using this proposed rules and a correlation engine, always within the IT Operations Monitoring domain, they can issue a notification that the solution for a potential issue has been detected. Now that this solution is on hand, the only thing remaining is for it to be executed, and usually by a Change Management Process that still has a high demand for human help.

7.1. Future Trends

Enterprise IT helpdesks can bridge the skill gap of support teams by upskilling end-users to address common technology issues on their own using Self-Service Troubleshooting capabilities. Proactive Issue Detection and Prevention capabilities can move the helpdesk function towards a predictive support model that reduces incoming tickets as well as improves end-user experience. Proactive insights can also help organizations to comply with regulatory requirements covering topics such as compliance monitoring and risk mitigating controls. However, the deployment of AI-Driven Autonomous Knowledge Assistants must not compromise enterprise Data Governance principles. Privacy protection of sensitive data and efforts to address bias during Data Ingestion and Wrangling are essential prerequisites. Dedicated and comprehensive assessment frameworks should measure the impact delivered by

these AI-Driven Autonomous Knowledge Assistants across Operational Performance and User Experience & Adoption metrics.

Several trends are expected to shape enterprise IT enablement operations in the next few years. Cloud-based self-help IT support resources will become increasingly popular and could drive enterprises to integrate content from third-party sites while enforcing specific content controls on information from these sites. Large Technology Players will continue to enhance query resolution capabilities on their Productivity and Collaboration platforms, covering Business Operation products and Equipment as well. AI and Machine Learning-based solutions will enhance Self-Service Troubleshooting capabilities and thereby, reduce inbound ticket volumes and expedite ticket resolution. Further advancements are likely to address sensitive regulatory and compliance needs and mitigate control gaps.

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